THE SOCIETAL COST OF OBESITY AND ITS BEHAVIORAL PRECURSORS: NEW ESTIMATES OF TIME-USE AND THE COST-EFFECTIVENESS OF A COACHING INTERVENTION TARGETED AT WOMEN IN MINORITY COMMUNITIES

by

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ABSTRACT

This dissertation examines the economic burden of being overweight and obese, paying particular attention to women as the obesity epidemic disproportionately affects women and cultural minorities. The overarching objective of this dissertation is to take a closer look at the indirect costs of obesity, particularly those pertaining to nonmarket costs, as measured by differences in household productivity and market costs, analyzed by assessing whether there is a correlation between occupational status and body mass index (BMI). The nonmarket costs of obesity are measured through time-use differentials by BMI strata, when controlling for cofactors related to housework. Results indicate that being overweight and obese is associated with less time spent on housework. Results indicate that the burden of obesity affects minority group women exactly the same way it does non-Hispanic White women.

After discussing the nonmarket and market indirect costs of obesity, the dissertation focuses on the economic benefits associated with a community-based coaching intervention aimed at increasing nutritious diets and physical activity among women in culturally diverse Utah communities. Little is known about the net economic effects of such targeted community-based interventions, and this dissertation seeks to contribute to the literature on this subject. Results show that the health intervention program is cost effective and that the wellness coaching intervention has helped increase healthful lifestyles, as measured by physical activity.

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CHAPTER 1

INTRODUCTION

The obesity epidemic is a widely recognized healthcare problem, especially in the United States. In the past 2 decades, both overweight and obesity rates in the United States have increased significantly, causing concern regarding the social and healthcare burden of this trend. There have been important contributions from the economics profession that have enhanced our understanding of the causes and consequences of the obesity epidemic. The literature on the matter is moving towards implementing health interventions and assessing their effectiveness. In order to implement successful health policies, understanding the costs of obesity is critical. This dissertation extends part of the literature on the indirect societal burden with a particular focus on women, and engages in an economic assessment of an ongoing intervention to increase physical activity and nutritional practices among minority communities of women in Utah.

Obesity is associated with type II diabetes, cardiovascular disease, sleep apnea, and certain types of cancers; those co-morbidities have increased with rising rates of obesity. Along with rising rates of obesity there have consequently been substantial increases in direct costs of obesity. Direct costs are estimated to be between $86 and $147 billion per year in the United States in 2006 (Finkelstein, Trogdon, Cohen, & Dietz, 2009). This translates into approximately 10% of annual medical spending. Though many factors contribute to obesity, two of the main areas of focus are individual behaviors, such as nutritional intake and amount of physical activity, and the built environment, which represents the working and living conditions that contribute to obesity risk (Caballero, 2007).

Obesity also has substantial indirect costs associated with it, including the cost of lost productivity. The economics literature has classified indirect costs as lost productivity arising from absenteeism, presenteeism, disability, premature mortality, and workers' compensation. Both indirect costs and direct costs vary by gender and race; women, in general, incur higher costs (both direct and indirect) for being obese in comparison to men. Indirect costs of obesity, such as discrimination in the workplace and lost productivity in the household, have as of yet not been quantified or analyzed.

There are also gaps in the literature related to health intervention programs and the degree to which they are successful. Researchers need to design, implement, and evaluate health intervention programs using multidisciplinary teams that can assess both the outcomes of these interventions and the associated costs. Providing such economic evaluations is helpful for public policy implementation as cost-effectiveness analysis is useful when deciphering if a health intervention yields good value for the money and is thus useful when making healthcare decisions. This dissertation seeks to address these gaps.

The purpose of this dissertation is to assess the costs of being overweight/obese by examining nonmarket and market indirect costs of obesity in the United States for women. Personal health choices and how they affect one's level of well-being are a central theme in this dissertation. Unlike previous studies, this dissertation focuses on whether differences in body mass index (BMI) levels have are associated with household time-use using a household production framework. Detailed analyses of race/ethnic differences in time use by BMI status are also provided. Finally, a cost-effectiveness analysis for a physical activity health intervention program that is directed at high risk minority women is presented. This dissertation is divided into four chapters: literature review (Chapter 2), indirect costs of obesity pertaining to nonmarket and market costs (Chapter 3), nonmarket costs of obesity specific to ethnic/racial groups (Chapter 4), and an economic evaluation of a local health intervention (Chapter 5).

The literature review focuses on economic factors of obesity, the costs associated with obesity and physical inactivity, and what gaps in the literature need to be addressed. In Chapter 3, I conduct an economic analysis of indirect costs by measuring nonmarket costs of being obese or overweight stemming from lost productivity in the household as measured by time-use differentials. Chapter 3 also provides an occupational status analysis of whether being overweight or obese has a correlation with occupational status, when controlling for education.

The goal of Chapter 4 is to assess whether time-use differentials, influenced by BMI strata, are different among racial/ethnic groups. That is to say, if there is an obesity-related time-use penalty, for example, is there a higher burden for minority group women? Specifically, the analysis focuses on whether being non-Hispanic Black, non-Hispanic Asian, or Hispanic leads to higher indirect costs as measured by differences in time spent on housework per day in comparison to non-Hispanic Whites.

Lastly, in Chapter 5 I conduct a cost-effectiveness analysis of a health intervention aimed at minority group women. The health intervention is centered on a wellness coaching intervention conducted through engaged community partnerships. The cost-effectiveness analysis assesses a wellness coaching program.

CHAPTER 2

LITERATURE REVIEW: COSTS OF OBESITY AND PHYSICAL INACTIVITY

2.1 Introduction

Health care expenditures in the United States have risen significantly in the last few decades; in 2010, health expenditures comprised 17.6% of gross domestic product (GDP), compared with only 7.2% of GDP in 1970 (Thorpe, Florence, Howard, & Joski, 2004). Though there are many factors contributing to increased health expenditures, increases in physical inactivity and obesity levels have greatly added to health care costs.[1] Physical inactivity, independent of its association with obesity, causes increases in health care expenditures but physical inactivity also contributes to rising obesity levels. Estimates show that roughly 74% of adult Americans fail to meet the recommended guidelines for a healthy amount of physical activity, which has been prescribed as 30 minutes of moderate-intensity activity on most days of the week (Garrett, Brasure, Schmitz, Schultz, & Huber, 2004).

Studies show that detrimental dietary intake (unhealthy nutritional intake) and physical inactivity rank second (to tobacco use) as a leading risk factor for all causes of

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[1] Obesity is defined as having a body mass index (BMI) greater or equal to 30, whereas normal-weight adults have a BMI ranging from 18.5-24.9, and overweight adults have a BMI ranging from 25-29.9. This does not hold true for all ethnic groups (i.e., Pacific Islanders).

death (Garrett et al., 2004), and diet and lack of physical activity contribute to around 14% of mortality rates (Colditz, 1999). Obesity is both a medical and economic phenomenon in that it causes deteriorating health conditions, many times leads to reduced life expectancy, and increases the prevalence of chronic diseases as well as disability (Sturm, Ringel, & Andreyeva, 2004). Not only does obesity affect morbidity but it also affects mortality rates; estimates show that around 400,000 deaths per year are associated with obesity in the United States (Finkelstein, Ruhm, & Kosa, 2005).

In an analysis of the trends in overweight and obesity, the Centers for Disease Control (2013) found that between 1960 and 1962, 44.8% of adults (20-74 years) were overweight or obese; by 1988-1994, this rate had increased to 56%; and between 2009 and 2012, the rate had increased further to 68.8% of the population. Specifically focusing on trends in obesity patterns, the obesity rate for the adult population (20-74 years) in 1960-1962 was 13.3%; by 1998-1994, the obesity rate had risen to 23.3% of the population; and by 2009-2012 the rate had increased to 35.7% of the population (Centers for Disease Control, 2013).

In 1960-1962, 11.2% of adults were Grade I obese (BMI between 30 and 34.9), 2.6% were Grade II obese (BMI between 35 and 39.9), and 1% of the population was Grade III obese (BMI greater or equal to 40). By 1988-1994, 14.8% of adults were Grade I obese, 5.4% were Grade II obese, and 3.1% were Grade III obese. By 2009-2012, 20.4% of adults were Grade I obese, 8.8% were Grade II obese, and 6.6% were Grade III obese (Centers for Disease Control, 2013). Hence, overweight and obesity rates rising and the degree to which they are rising is also increasing as Grade III obesity levels have risen substantially over the last few decades.

Physical inactivity and obesity not only place heavy health burdens on individuals, but they also have significant economic and societal impacts. Obesity imposes two types of health-related costs: direct costs resulting from the treatment of morbidity and the increase in medical expenditures, and indirect costs caused by lost productivity and lost earnings attributable to premature mortality.[2] The societal burden is defined as the sum of both the direct and indirect costs that are associated with obesity and associated risk factors. Direct costs are measured by medical expenditures associated with being obese, which stem from increased health care utilization. Though the direct costs of obesity have been well established, indirect costs have not been as commonly measured in the literature.

In order to understand the full economic and societal burden of overweight and physical inactivity, the literature review discusses the causes of obesity, specifically the economic factors contributing to rising obesity rates. Next, the literature addresses the direct costs of obesity and physical inactivity. Then the literature review focuses on the indirect costs of obesity. Although many studies have contributed to the literature regarding the economic costs of obesity, there are gaps pertaining to the indirect costs literature that this dissertation seeks to fill. Given that this dissertation focuses on an economic analysis of a health intervention program, an additional literature review was conducted that outlines types of health intervention programs and what cost-effectiveness analysis is.

[2] Two other costs that are potentially associated with obesity are transportation and human capital costs.

2.2 Causes of Obesity

A person is classified as obese if they have excess body fat. The labels "overweight" and "obese" are used to indicate a weight that is greater than what is considered a healthy weight, when taking height into account. For adults, these ranges are determined by using weight and height to calculate body mass index (BMI) levels, which are then used for classification. BMI is used because, for most people, BMI correlates with their amount of body fat. As BMI does not directly measure body fat, this is a limitation when using BMI to classify if an individual is overweight or obese. Thus, it is possible that some individuals are classified as overweight when in fact they are not (CDC, 2014).

The obesity epidemic is not only a health phenomenon, but to a great extent an economic one because increased caloric consumption and decreased energy expended are economic in nature. Economic changes have altered the costs of food production. Also, the time and monetary cost of food consumption has decreased. Factors contributing to rising obesity rates have come about due to changes in technology, food prices, rises in wages, and the rise in the maternal employment rate (Finkelstein et al., 2005). Hence, both environmental and technological changes are contributing factors to the dramatic increase in obesity in the last 30 years, and also why it has increasingly become more difficult for individuals to maintain a healthy weight and a healthy lifestyle. Simultaneously, the real costs of being physically active have increased while the health consequences that stem from obesity have decreased. Health consequences of obesity have decreased because of new drugs, procedures, and devices that help manage the adverse health effects of obesity (Finkelstein & Strombotne, 2010).

Technological improvements have reduced energy expended by employees in the workplace, and thus reduced number of calories burned per day; though technological advances have led to increases in productivity in the workplace and in the home, they have also led to decreases in energy expenditures, which have increased obesity rates (Lakdawalla & Philipson, 2002). Medical improvements and advances have also decreased individual health costs of obesity, which may lead to a decreased motivation to embrace a proper diet and exercise. The health consequences that stem from being obese have decreased due to new drugs, procedures, and devices that manage the adverse health effects of obesity (Finkelstein et al., 2010). The number of calories consumed has increased as a direct result of technological advancements that have reduced food prices for energy-dense foods. Health experts have noted that this increase in energy intake is sufficient to explain the rise in body weight, especially since most of the increase in energy consumed stems from the intake of carbohydrates (Centers for Disease Control and Prevention, 2004).

According to consumer price index (CPI) data, food prices rose 3.4% per year from 1980-2000; however, during this same period the average rise in the inflation rate was 3.8%, meaning that food prices rose less rapidly. Also, since the relative prices of calorie-dense foods and beverages have decreased since the 1980s in comparison to less energy-dense foods, such as fruits and vegetables, consumers have gravitated toward the cheaper foods (Finkelstein et al., 2010). Analyzing price changes, data show that between 1985 and 2000 prices for fresh fruits and vegetables, fish and dairy production increased by 118%, 77% and 56%, respectively, while the prices of sugar and sweets, fats and oils, and carbonated beverages have only increased by 46%, 35% and 20%, respectively

(Finkelstein et al., 2005). The unequal increase in prices is due to advances in food technology that disproportionately affect processed foods. Hence, if the price of healthy food rises, a substantial portion of the population will decrease their consumption of healthy foods and increase the consumption of cheaper, and generally speaking, more unhealthy food options. This is especially true for lower socioeconomic groups because changes in food prices have a significant impact on their household budgets.

Other economic factors contributing to increased obesity rates are increased wages and increased maternal employment. These two factors have contributed to rising obesity rates because they have led to increased consumption of prepackaged and/or fast foods, both of which have a positive correlation with weight gain. Also, increasing female labor force participation contributes to rising obesity rates because of changes in how women spend their days. Female labor force participation rates have changed time allocation choices, as well as patterns in food consumption (Bleich, Cutler, Murray, & Adams, 2008). Female labor force participation has led to changes in the "traditional roles" of the household. For example, increased maternal employment has been shown to increase childhood obesity, as women in the workforce are less likely to prepare home-cooked meals (Finkelstein et al., 2005).

2.3 Direct costs due to obesity

Direct costs of obesity are those resulting from medical expenditures stemming from utilization of medical services; health care utilization increases stemming from obesity are primarily due to increases in inpatient services, noninpatient services, and pharmaceutical prescriptions (Finkelstein, Trogdon, Cohen, & Dietz, 2009). In 2009, roughly 145 million Americans lived with one or more chronic health care conditions; overweight and obesity are major risk factors for many of these chronic diseases. Rising obesity rates have contributed to the increased prevalence of comorbidities, such as type II diabetes, hypertension, cardiovascular disease, hypercholesterolemia, asthma, sleep apnea, musculoskeletal diseases, stomach ulcers, gallbladder diseases, chronic liver disease, and certain types of cancer (Colditz, 1992). Obesity during pregnancy has also been linked to health-related problems in children. Hence, rising obesity rates have increased health care and medical care expenditures through direct costs as there are increased treatments of obesity-related chronic diseases (Thorpe & Philyaw, 2012).

Chronic health care conditions consume about 78% of national health care expenditures (Thorpe et al., 2012). However, obesity has not been linked to a substantially shorter life span; elderly patients who are obese generally spend 40% more of their remaining life years in disability, in comparison to their normal weight counterparts (Thorpe et al., 2012). Obese adults average 48% more inpatient days per year in comparison to those of normal weight, 38% more primary care physician visits, 1.84 times the annual number of pharmacy dispenses, six times the number of dispenses for diabetes medication, and 2.4 times the number of dispenses for cardiovascular medications than nonobese adults (Finkelstein et al., 2005).

Recent estimates, using the Medical Expenditure Panel Survey (MEPS) data, indicated that obesity has caused an approximate $147 billion increase in medical spending (Finkelstein et al., 2009).[3] This study also showed that obese adults incur annual medical expenditures that are 37% higher than expenditures for normal-weight

[3] This study used regression analysis with controls for demographic variables, smoking status and insurance status to draw conclusions.

individuals (Finkelstein et al., 2009). The average increase in annual medical spending associated with obesity is 37.4% ($732) and ranges from 26.1% ($125) for out-of-pocket to 36.8% ($1,436) for Medicare and 39.1% ($864) for Medicaid. Even though it is the obese individual who directly bears the health risks associated with obesity, the costs of the treatment of obesity-related diseases are shared by society (Finkelstein et al., 2010). For obesity-related diseases, the per capita spending by weight category shows that, in 2009 dollars, those who had normal weight spent $1,090 per capita, whereas those who were overweight spent $1,390, obese individuals spent $2,030, and those who were morbidly obese spent $2,770 per capita. Thus, spending for these groups was 27.52%, 86.23%, and 154.13% higher, respectively, in comparison to normal weight (Congressional Budget Office, 2010).

Measured as per capita medical spending, in 1998, those who were obese spent $1,145 more than normal-weight people and by 2006 that amount increased to $1,429 (Finkelstein et al., 2009). This increase in per capita spending translates into increased spending in terms of insurance. The Medicare program saw a 36% increase in spending due to obesity, previously spending $1,006 per person and now $1,723. Medicaid went from spending $284 per person to $1,021, a total increase of 47% in annual costs. Lastly, private payers went from spending $957 to $1,140, a total increase of 58% in annual costs (Finkelstein et al., 2009).

The rising prevalence of obesity, and hence higher relative per capita spending for obese people, is said to have accounted for 27% of the growth in real per capita health care spending between 1987 and 2001 (Thorpe et al., 2004). In 1990, the total direct costs, which were computed by summing the expenditures of coronary heart disease, hypertension, gallstones, and noninsulin-dependent diabetes mellitus, per BMI group were as follows: for those whose BMI was between 23 and 24.9, total expenditures were $5.89 billion; for those with BMI between 25 and 29.9, expenditures amounted to $12.06 billion; and for those whose BMI level was 30 or over; total direct costs amounted to $22.62 billion (Wolf & Colditz, 1996). This study concluded that had, in 1990, the United States prevented obesity, around $45.8 billion could have been saved in 1990 (Wolf et al., 1996).

Focusing on the link between obesity prevalence and increases in spending over time, one study found that in 1987, the average per capita spending on medical expenditures was $2,188 and spending for those who were obese was 15% higher than for those with normal weight ($2,438 versus $2,117, respectively). However, by 2001 the average per capita spending increased to $3,298, which is roughly a 50% increase in per capita spending. Analyzing the differences in weight category, those who were obese spent $3,979 per capita, whereas those who were normal weight spent $2,907 per capita; hence spending for obese people was 37% higher than those of normal weight (Thorpe et al., 2004).

For the medical conditions linked with obesity, there has also been a stark increase in the number of cases: diabetes cases increased by 79% and hypertension by 29% between 1987 and 2001 (Thorpe et al., 2004). In 2001, the per capita spending for those with normal weight and diabetes was $58 per person, whereas for those with obesity it was $193. That same year, spending for those with normal weight and hyperlipidemia was $34 per person, whereas it was $78 for those who were obese. The starkest differences could be seen for those with heart disease; in 2001, the per person expenditure for those with normal weight was $276; however, the cost for those who were obese was $514 per person (Thorpe et al., 2004).

More current estimates of medical expenditures per capita show that in 2007, normal- weight adults spent $4,030 per capita, whereas those who were overweight spent $4,260, those who were obese spent $5,560, and those who were morbidly obese spent $7,010. This means that in comparison to normal-weight adults, per capita expenditures were 5.70%, 38%, and 74% higher, respectively.

Most studies using regression analysis conclude that total burden of obesity for the United States in terms of medical expenditures lies anywhere between $86 billion annually, based on MEPS data, and $147 billion using the National Health Expenditure Accounts (NHEA) data. Overall, the annual medical burden of obesity has increased from 6.5% to 9.1% of annual medical spending (Finkelstein et al., 2009). However, a stark limitation in regard to this measurement is that direct costs are estimated by measuring the resources used and are, in most cases, derived strictly from comorbidities, such as diabetes, cardiovascular disease, and respiratory disease rather than obesity and/or physical inactivity.

Another limitation to these studies is that BMI is not a direct measure of body fat in that it does not distinguish fat from muscle and does not identify how body fat is distributed. When using national surveys, such as the Behavior Risk Factor Surveillance Survey (BRFSS) and MEPS data, estimates rely on self-reported data and exclude institutionalized populations. Using self-reported data is likely to cause underreporting of weight, and thus may bias the regression coefficients. This issue is more important to keep in mind when using continuous measures of BMI rather than the categorical measures of BMI (e.g., normal weight, overweight, and obese).

One of the biggest limitations of the studies previously described is that they do not address the issue of endogeneity as they do not examine the causal effect of obesity on medical care costs; obesity can lead to injury or depression, hence increasing medical care costs but on the other hand, injury or depression, can lead to obesity. Hence the correlation is an overestimate of the causal effect if, for example, some people became obese after suffering injury or chronic depression, and therefore have higher medical costs.

Only one study, Cawley and Meyerhoefer (2010), addresses the fact that BMI may be an endogenous factor, and thus any regression analysis should incorporate an instrumental variables approach. This study uses the weight of a biological relative as the instrument. Cawley and Meyerhoefer use data provided by MEPS and show that previous studies may have greatly underestimated the effect of obesity on medical care costs. Endogeneity arises in econometric models if an explanatory variable is correlated with the error term; endogeneity arises due to omitted variables, measurement error, and simultaneity (Wooldridge, 2002). Simultaneity occurs when an explanatory variable is determined simultaneously with the dependent variable of a statistical model (Wooldridge, 2002). When studying the economic costs of obesity, simultaneity issues can occur if, for example, studies do not take into account that obesity can cause comorbidities, whereas on the other hand, having a comorbidity could lead to obesity.

Cawley and Meyerhoefer concluded that for men, 79% incurred some medical expenditures in the survey year (2005), and unconditional average medical expenditures in that year were $1,999 (in 2005 dollars). For women, the authors concluded that 88%

incurred some medical expenditures, and unconditional average medical expenditures in that year were $2,617. The total effect of obesity on medical care costs was $3,115. Previous studies not using the instrumental variables approach showed estimates of $1,429. The authors concluded that national medical care costs due to obesity are $185.7 billion, more than twice the estimate of previous studies. Hence, direct costs of obesity may amount to 16.5% of national health expenditures in the United States.

The limitation of the Cawley and Meyerhoefer study is that since one of the instruments used for the instrumental variables analysis is the weight of a biological relative, the study analyzes only adults with at least one biological child and hence may not be an accurate reflection of the total population. Also, as with all instrumental variables analysis, the instrument used is a concern because of validity, even though their instrument passes the tests for power and over-identification.

2.4 Direct Costs due to Physical Inactivity

Obesity is a major contributing factor to health care costs; however, another important contributor is the cost of a sedentary lifestyle (distinct from its correlation with obesity). Physically inactivity has been linked to coronary heart disease (CHD), hypertension, stroke, colon cancer, breast cancer, lung cancer, osteoporosis, noninsulin-dependent diabetes, low back pain, obesity, depression, and anxiety (Haskell et al., 2007).[4] Fifty-one percent of adults (18 years and older) in the United States did not meet the recommended level of moderate intensity physical activity in 2005 (Oldridge, 2008).

[4] Physically active is generally defined as spending at least half an hour in moderate or strenuous physical activity three or more times per week; physically inactive is defined as not meeting these guidelines. However, the CDC's guideline for being physically active is at least 150 minutes of moderate-intensity aerobic activity per week.

Studies indicate that in 1990, between 14% and 23% of all deaths were attributed to diet and activity patterns in the United States (Pratt, Macera, & Wang, 2000). Pratt et al. also found that if 10% of sedentary adults began a walking program, anywhere between $4.3 and $5.6 billion could be saved annually. Though estimates vary, after adjusting for BMI, roughly 11.1% of aggregate health care expenditures stem from inadequate levels of physical activity (Carlson, Fulton, Pratt, Yang, & Adams, 2015). Before adjusting for BMI, physical inactivity accounts for approximately $131 billion per year; after adjusting, physical inactivity accounts for roughly $117 billion per year.

Men are more likely than women to meet the recommendation, (50.7% versus 47.9%, respectively). Non-Hispanic Whites were most likely to meet the guidelines (51.1%), followed by "other" racial or ethnic groups (46.3%), Hispanics (44.0%), and African-Americans (41.8%) (Haskell et al., 2007). Educational levels also affect the likelihood of meeting the recommended guidelines as those with higher levels of education are more likely to meet the guidelines; 53.2% of those with a college degree met the guidelines, whereas only 37.8% of those who have less than a high school degree met the guidelines (Haskell et al., 2007).

Sedentary lifestyles were estimated to contribute $24.3 billion per year to direct costs; the cost per inactive person was estimated to be around $760 (Colditz, 1999). More current estimates on the matter suggest that, per capita, those who are physically active spend about $1,000 less in annual medical care services than their inactive peers, which translates to a cost savings of $76.6 billion annually if those who were inactive became active (Wang, Pratt, Macera, Zheng, & Heath, 2004).

Using the 1987 Medical Expenditures Panel Survey (MEPS) data and respondents who were 15 years or younger, Pratt et al. (2000) found that those who were active had annual costs of $1,242 on average while those who were inactive had average annual costs of $2,277. The authors stratified the sample based on the presence of physical limitations. Data from the MEPS also show that those without physical limitations and who are active have annual direct medical costs of $1,019, whereas those who are inactive have costs of $1,349. The authors, however, do not indicate whether they tested for potential endogeneity issues.

When analyzing the costs associated with physical inactivity by age group, the study showed that in every age group, those who were physically active had lower medical costs than those who were physically inactive (Pratt et al., 2000). The study concluded that there were positive results for those who had physical limitations, but were moderately physically active, versus those with physical limitations and inactive (Pratt et al., 2000). The authors noted that around $76.6 billion (in 2000 dollars) could be saved per year in direct medical costs if all inactive persons were to become active.

Another study that analyzed the cost of physical inactivity for American adults concluded that a 5% reduction in the number of those who were physically inactive and overweight would amount to a cost savings of $31 billion per year (Chenoweth & Leutzinger, 2006). The costs were a composite of medical care costs, workers' compensation costs, and lost productivity costs. Limitations to this study include that the study analyzed costs of physical inactivity and excess weight for residents of seven states (California, Massachusetts, Michigan, New York, North Carolina, Texas, and Washington) and then, from the results of those seven states, applied estimates to the United States as a whole. The authors believe that since these seven states consist of roughly 77 million adults and represent different geographic regions, they represent different demographic profiles, risk factor prevalence rates, and medical care cost inflation trends (Chenoweth & Leutzinger, 2006). This study concluded that roughly \$92.32 billion per year was spent due to physical inactivity in the seven states; hence applying this figure to the United States' population as a whole amounted to \$251.11 billion per year. These costs are substantially higher than previous estimates, which may be a direct reflection of the estimation from seven states applied to the nation on the whole.

Specifically analyzing the population of Minnesota, data from the Blue Cross Blue Shield program were used to estimate the direct costs of physical inactivity. Overall, Garrett et al. (2004) found that the most expensive outcome of being physically inactive was heart disease, with expenditures amounting to \$35.3 million in 2000. According to their study, total expenditures for the health plan that were a direct result of physical inactivity amounted to \$83.6 million for inpatient, outpatient, and pharmacy claims. Hence for their study population, the per capita costs due to physical inactivity were \$56 per year. However, Garrett et al. reported that these results are not comparable to other studies since their analysis included different conditions and actual paid amounts rather than the charges, and the study population may have been healthier on average as they were part of a health plan.

Using data from the National Health Interview Survey (NHIS) merged with the MEPS data in an examination of total health expenditures (not incorporating indirect costs), Carlson et al. (2014) used four econometric models in order to ascertain health care expenditures due to physical inactivity. After adjusting for cofactors, this analysis estimated that, on average, inactive adults had $1,437 higher mean annual expenditures than active adults, and those who were insufficiently active had $713 higher mean annual expenditures than those who were active (Carlson et al., 2014). When including BMI as a cofactor, inactive adults had $1,313 higher mean annual expenditures than active adults, and those who were insufficiently active had $576 higher mean annual expenditures than those who were active (Carlson et al., 2014).

In 2001, the economic cost of cardiovascular disease (CVD) was estimated at $298.2 billion, of which $181.8 billion is direct medical costs (Wang et al., 2004). The economic costs of CVD associated with inactivity show that for men the correlation between inactivity and CVD prevalence was not statistically significant, whereas for women inactivity was associated with higher rates of CVD. In comparing the expenditures for those who had CVD and were inactive with those who were active, expenditures for women were higher than for men except in the category for inactive with CVD. The average per capita annual medical expenditures for persons with CVD was $3,784 for those who were active; however, those with CVD and who were inactive had annual per capita medical expenditures of $6,313.

Wang et al. (2004) do not indicate whether this outcome was age-adjusted, income-adjusted, and adjusted for race or ethnicity. Though the authors have stratified the outcomes by body weight, smoking status, and age, the methodology section does not indicate whether the medical expenditures (per capita) by the population are adjusted for any potential cofactors. Also, it would be interesting to see how gradients of inactivity matter: the study looked solely at inactive versus active persons. However, insufficiently active would be another category that could be included to make comparisons.

2.5 Indirect Costs of Obesity

Indirect costs encompass both the value of lost health as well as the value of lost vitality caused by morbidity (Colditz, 1996). Indirect costs are measured by lost productivity due to a health condition and include the following categories: absenteeism (measured by the number of days spent absent from work), presenteeism (measured by being physically present at work, but not being as productive), disability, premature mortality, and workers' compensation (Trogdon, Finkelstein, Hylands, Dellea, & Kamal-Bahl, 2008). Other indirect costs identified in the literature pertain to loss of quality-adjusted life years, higher rates of disability benefit payments and welfare losses in the health insurance market (Hammond and Levine, 2010).

Workers' disability adds to indirect costs as obese employees tend to have longer-term disability in comparison to their nonobese peers. Furthermore, as obesity has not been shown to reduce the lifespan much, disability due to obesity-related cardiovascular diseases will increase in industrialized countries because the survival rate for cardiovascular diseases has been increasing (Visscher & Seidell, 2001). Premature mortality and workers' compensation add to indirect costs because employers will have the increased burden of life insurance costs (Trogdon et al., 2008).

Absenteeism contributes to indirect costs as it relates to number of days of missed work due to illness or injury; on average, obese workers miss more days from work (short-term absences). Increased indirect costs attributable to obesity have significant effects for the workforce because they present an obstacle in providing affordable health insurance to employees and because obese workers have higher rates of absenteeism (Finkelstein, DiBonaventura, Burgess, & Hale, 2010). Obese workers miss more days from work and have longer-term disability in comparison to their nonobese peers. Data show that annual missed workdays were 0.5 more days for overweight men, 1.6 more for Grade I obese men, 3.8 more for Grade II obese men, and 5.9 days more for Grade III obese men; for women, data show that annual missed workdays were 1.1 more days for overweight women, 3.1 more for Grade I obese women, 0.5 more for Grade II women, and 9.4 days more for Grade III obese women (Finkelstein, DiBonaventura, Burgess, & Hale, 2010).

The literature on indirect costs is primarily based on self-reported absenteeism measures, and hence the estimates may not be truly reflective of actual estimates. Currently, estimates of absenteeism for the United States range anywhere from 3.38 billion dollars annually ($79 per obese person) to $6.38 billion ($132 per obese person). Depending on the gender and obesity category, the costs associated with absenteeism ranged from $77 per person to $1,033 per person (Trogdon et al., 2008).

Disability is the second type of indirect cost associated with obesity. Disability is defined as the time away from work that involves a disability claim or disability payments, which are, generally speaking, financed by insurance policies in the United States, whereas in Europe they are generally financed by the government. Data from European countries made it possible to analyze the disability costs attributable to obesity using a cohort study from countries such as the United Kingdom, Belgium, and Sweden. What was found in these studies was that the odds ratio for missed work due to a disability for obese persons relative to nonobese persons ranged from 1.15 to 2.8 (Trogdon et al., 2008).

Only three studies have reported obesity-attributable costs separately from premature mortality. Indirect costs associated with lost earnings from premature mortality in the United States amounted to around $30 billion, or $625 per obese person. In comparison, increased life insurance costs due to obesity amounted to $2.53 billion, or $59 per obese person (Trogdon et al., 2008). Workers' compensation is measured as payments made to employees due to workplace accidents or injuries. From the data, it has been shown that the rate ratio of claims was between 1.21 and 1.45, depending on the category of obesity, whereas the rate ratio for lost work days was between 3.39 to 8.04, and the rate ratio for income replacement claims ranged from 2.95 to 7.71 (Trogdon et al., 2008). Presenteeism measures reduced productivity at work caused by obesity. Studies pertaining to presenteeism have mixed results, as the data for the three studies that attempted to analyze the cost of presenteeism are different. One of the studies indicated that obese workers were 98.5% as productive as nonobese workers, whereas another study indicated that presenteeism costs were around $9.1 billion per year, which translates to about $350 per obese employee (Trogdon et al., 2008).

Analyzing differences in presenteeism for every BMI category except overweight men, presenteeism caused additional costs. For example, overweight women had 0.9 days associated with presenteeism and Grade III women had 22.7 days associated with presenteeism; this amounts to $121 incremental costs for overweight women (in comparison to their normal weight counterparts) and $3,037 for grade III obese women (Finkelstein et al., 2010). Aggregate expenditures for overweight women amount to $4.9 billion and for Grade III obese women, it totals $15 billion (Finkelstein et al., 2010).

The Finkelstein et al. study (2005) focused on four categories of obese men and women who were employed full-time: overweight, Grade I obesity, Grade II obesity, and

Grade III obesity, with the goal of assessing if there were substantial differences between BMI strata. The costs associated with obesity were divided as follows: for indirect costs, the costs were measured as the dollar value for annual missed work days due to illness or injury; for medical expenses, the costs included annual spending for office-based visits, hospital outpatient and inpatient visits, emergency room visits, dental visits, home health care, vision aids, medical and services equipment, and prescribed medicines. The samples came from the National Health Interview Survey (NHIS) for 2001 and 2002 and the Medical Expenditure Panel Survey for 2000 and 2001. The sample size was restricted to adults, age 18-64, who were employed full-time (working 35 hours or more a week); however, the dataset did not include pregnant women.

Finkelstein et al. (2005) used the data from the NHIS in order to predict obesity-attributable absences that stemmed from illness or injury. Using regression analysis, the authors estimated missed work days separately for men and women. In order to predict the impact of excess body weight on annual missed work days, they included dichotomous variables in the regressions that indicated the adult's BMI category. The MEPS dataset was used to calculate the costs associated with increased medical expenses as the dataset includes both body measurements and annual expenditures, meaning that a direct analysis of the relationship between BMI and medical spending is possible. The authors used a four-equation regression approach in order to predict the annual medical expenditures, separating men and women and running it via the BMI categories.

The results of the regression analysis show that for men 70% of the full-time employed population was either overweight or obese, whereas 53% of women were classified as either overweight or obese. The authors note that the substantial difference between the two may stem from the fact that there is a much higher self-reported prevalence of overweight among employed men (Finkelstein et al. 2005). The results from the NHIS dataset show that normal-weight men miss approximately 3 days of work each year due to illness/injury. However, men with Grades II and III obesity miss 2 more days of work per year. For women, the results show that normal-weight women miss, on average, 3.4 days per year, whereas overweight women miss 3.9 days, women with Grade I obesity miss 5.2 days, with Grade II obesity it amounts to 6.4 days, and with Grade III obesity, 8.2 days per year are missed.

The sample used in the Finkelstein et al. (2005) article consisted only of fully employed individuals. In terms of the number of missed days of work, men who had a normal weight missed on average 3 days of work per year, whereas those with Grade I obesity missed 3.3 days on average, and those with Grades II and III obesity missed 4.9 days, each. However, for women the differences in missed days of work with increased weight are far more dramatic. Normal weight women missed 3.4 days a year on average, whereas those with Grade I obesity missed 5.2 days, Grade II obese women missed 6.4 days, and those with Grade III obesity missed 8.2 days, on average (Finkelstein et al., 2005).

In terms of the economic burden this places on society, Finkelstein et al. (2005) concluded that the costs of absenteeism, per capita, for men were as follows: $6 for overweight men, $70 for Grade I obese men, $643 for Grade II obese men, and $436 for Grade III obese men. For women, costs due to absenteeism were higher in every category in comparison to men. Overweight women had $93 in absenteeism costs, $302 for Grade I obese women, $936 for Grade II obese women, and $805 for Grade III obese women.

In terms of medical expenditures plus the costs of absenteeism, men were less costly in every single category in comparison to women. Overweight men had total costs of $175, whereas overweight women had total costs of $588; for those with Grade I obesity, men totaled $462, whereas women totaled $1,372; for those with Grade II obesity, men totaled $1,212, whereas the women totaled $2,485; lastly, for those with Grade III obesity, men totaled $2,027, whereas the women totaled $2,169 (Finkelstein et al. 2005).

Annual per capita medical expenditures by BMI category showed that normal-weight men incur costs to employees of about $1,351 per year, whereas women incur costs of $1,956. Medical expenditures and the dollar value of increased absenteeism range from $175 for overweight men (where $169 is from increased medical expenditures and $6 is from increased work loss) to $2,027 per Grade III obese males (with $1,591 from increased medical expenditures and $436 from increased work loss). For women, expenses ranged from $588 for those who are overweight to $2,485 for those women with Grade II obesity.

Updating these results to include the costs of presenteeism, using data from the 2006 MEPS and 2008 National Health and Wellness Survey, shows that indirect costs of obesity (and overweight) rose. Again, differences in absenteeism can be seen not only for gender, but also for BMI strata. Overweight men miss, on average, 0.5 days, whereas Grade III obese men miss 5.9 days more than their normal weight counterparts; in comparison, overweight women miss 1.1 days more and Grade III obese women miss 9.4 days more (Finkelstein et al., 2010).

Per capita expenditures for presenteeism and absenteeism costs showed that overweight men spend $322 less, Grade I obese men spend $1,143 more, Grade II obese men spend $2,491 more and Grade III obese men $6,087 more than normal weight men. Total per capita incremental costs for women are as follows: overweight $797, Grade I obese women $2,524, grade II obese women $4,112 and Grade III obese women $6,694 (Finkelstein et al., 2010).

Several limitations exist in the indirect costs of obesity literature. One such limitation is that the indirect costs are measured only for those who are in the workforce and not for those outside of it, such as stay-at-home mothers. As mothers, in general, are the vortex of family decisions in terms of eating and other behaviors, analyzing how obesity affects household production should be included in the literature as it not only has indirect costs associated with it, but there are numerous spill-over effects (such as the influence mothers have in terms of children's eating and exercise habits).

Another limitation is that the data used in these studies, specifically MEPS, to measure the costs of absenteeism do not specify why the subjects missed work. Therefore if a single mother was fully employed and obese but had a sick child, she may have had to miss work due to the child's sickness and not her own. Also, when analyzing the total costs of obesity (meaning the summation of direct and indirect costs), estimates from the literature seem to be on the conservative side since many of the indirect costs described above do not have associated dollar estimates due to lack of data. As with the literature on direct costs of obesity, the conclusions drawn from the studies may show biased results as they do not account for endogeneity.

2.6 Conclusion

The economics literature has contributed greatly to our understanding of the direct costs of obesity-specific diseases. However, there are gaps in the literature regarding the indirect costs of obesity, costs related to physical inactivity, and gaps relating to racial/ethnic differences in costs. In conducting the literature review on indirect costs, it became apparent that the estimates of annual costs do not take into account the costs associated with nonmarket costs. These are potentially significant added costs associated with obesity that should be incorporated into the literature. Another critical component that many of the studies do not focus on, potentially due to data limitations, is how costs vary by race/ethnicity.

After conducting the literature review, it also became apparent that only one study to date has accounted for potential endogeneity. Many studies that discussed the direct costs of obesity utilized the same dataset but drew different conclusions, partly stemming from different econometric techniques. Not accounting for endogeneity issues has the potential to cause substantial variations in the results. BMI, as noted in the literature, is very likely to be an endogenous factor. Hence, when conducting the econometric analysis for the nonmarket costs of obesity in Chapter 3 and Chapter 4, it is pertinent to first establish whether BMI is an endogenous variable, and if it is, use the correct econometric technique so as to have unbiased estimates.

The goal of the dissertation is to provide an investigation of indirect, nonmarket costs of obesity and overweight. The focus will be on establishing whether there are household productivity differences by BMI levels. If a penalty is established, this should be incorporated into the literature because nonmarket costs are important as there are many spillover effects that, although they cannot be measured in this study, potentially have significant social and economic outcomes. Also, the analysis will concentrate on the correlation between occupational prestige and BMI strata in order to assess if there is a link between the two. Few studies focus on costs of obesity by race and ethnicity, thus another goal of the dissertation is to ascertain nonmarket costs of obesity and overweight by race and ethnicity. Lastly, the dissertation will focus on conducting a cost-effectiveness analysis for a local health intervention program.

CHAPTER 3

NONMARKET AND MARKET INDIRECT COSTS OF BEING OVERWEIGHT AND OBESE AMONG WOMEN

3.1 Introduction

The goal of this chapter was to ascertain additional indirect costs associated with being overweight or obese which have not been previously assessed in the economics literature e, specifically concentrating on women. Indirect costs are defined as resources forgone as a result of a health condition; in this particular case, the health condition analyzed was being obese or overweight. Being overweight or obese is assessed by an individuals' body mass index (BMI); normal weight is defined as a BMI between 18.5 and 24.9, overweight is a BMI between 25 and 29.9, and obese is a BMI greater or equal to 30.[5]

In the first section, the analysis assessed indirect costs of obesity related to nonmarket activities. This was determined by analyzing household productivity, as measured by time use, in order to determine if productivity varies by BMI strata. The analysis focused on total time spent in housework and performing other household-related activities that have the potential to be related to energy balance. It should,

[5] Obese Grade I is defined as a BMI between 30 and 34.9, obese Grade II is defined as a BMI between 35 and 39.9, and obese Grade III is defined as a BMI greater or equal to 40.

however, be noted that a person's productivity in housework, using the output measure such as number of meals provided each day, is only imprecisely measured by time use.

"House management activities" or "core housework" activities are typically defined as total amount of time spent in preparing food, general cleaning, and clothing maintenance (Archer et al., 2013). Although the average amount of time spent in housework has been declining over the past 50 years, still 83% of American women conduct housework activities, and on the days where women engage in household activities, they spend an average of 2.6 hours on these activities (Bureau of Labor Statistics (BLS), 2013). For the current analysis, house management activities (described as total housework) were defined as total time spent in those activities plus time spent in general childcare.

In the second section, the analysis assessed if there is a correlation between being obese or overweight and market outcomes, as captured by occupational prestige. This was measured by analyzing whether occupational rankings are associated with a woman's BMI level, *ceteris paribus*. Both nonmarket activities and market activities were examined using data from the American Time Use Survey (ATUS), where nonmarket activities were measured through a time-use perspective analyzing differences in average time spent in total daily household production.

In the economics literature, the costs of obesity (and/or being overweight) are categorized as direct and indirect. Direct costs are those that accrue due to resources used because of a medical condition. Indirect costs are associated with lost productivity and are measured by labor market productivity regarding costs related to absenteeism, presenteeism, workers' compensation, workers' disability, and premature mortality. After conducting a literature review on the costs of obesity, gaps in the literature are present regarding indirect costs. Indirect costs, as currently discussed in the economics literature, are based solely on the penalties that occur in the workplace; thus, they do not take costs such as lost productivity at home and occupational costs into account.

One major limitation in measuring indirect costs this way is that it does not take into account the possibility that the occupation one has is influenced, either directly or indirectly, by an individual's BMI level, nor does it take other areas of lost productivity into account as it is focused only on market-related activities. The current literature, therefore, does not address whether a woman's time spent in household production nor whether occupational status is influenced by one's BMI. Such limitations may lead to an underestimation of the total societal burden of obesity. For example, wage penalties, imposed by high BMI are not accounted for as an "indirect cost," according to the literature. Studies show, however, that women are discriminated against in the workplace due to stigmas regarding weight, as seen through reduced wages in comparison to their normal weight counterparts (Cawley, 2004; Lempert, 2007). For example, Cawley (2004) estimated that an increase of two standard deviations from the mean weight was associated with the following: a 9% decrease in wages for non-Hispanic White women, a 4.7% decrease in wages for non-Hispanic Black women, and a 6.8% decrease in wages for Hispanic females. Thus, even though this is a cost imposed on obese women, it is not included as an indirect cost of obesity, *per se*.

In this chapter, the additional indirect costs associated with being overweight and obese were assessed by analyzing differences in household productivity. Lost productivity in the household was measured by examining differences in time spent in household activities, *ceteris paribus*. Other indirect costs potentially related to being overweight and obese arise if there is an association between occupational ranking and BMI (i.e., having a high-ranking occupation is more likely if one is normal weight); if there is such an association, this was classified as "occupational costs."

Research indicates that there is substantial weight discrimination in the United States (Puhl, Andreyeva, & Brownell, 2008). "Occupational costs" is the measurement of the indirect costs for having one's occupational choices limited due to one's BMI, holding education constant. For instance, a woman may be qualified for a multitude of jobs but because of the way she looks, she forgoes the opportunity to explore the options and opts, instead, for a lower paying job. Studies indicate that looks (beauty) and weight matter when getting hired. The literature suggests that this discrimination stems from potential employers excluding women from particular jobs based on their appearance or weight, but studies also show that the expectation of such practices may alter the job search process on the part of some women. Wages for average-looking people are higher than wages for those with below-average looks, whereas there is a premium for good-looking people (Hamermesh & Biddle, 1994). Society favors the beautiful (Hamermesh, 2013).

3.2 Utility Analysis and Housework

3.2.1 Time Spent in Housework

A standard definition of housework is the production of goods and services for own-consumption that could have been produced by hiring a third party to produce them had household members not done so (Reid, 1934). For instance, cooking dinner is considered housework since the household could have hired a third party to do the job; on the other hand, watching TV is not considered housework as it is considered a nonproductive (i.e., leisure) activity that can be carried out only by the person performing the activity.

In practice, housework is generally measured by time spent in meal preparation and cleanup, cleaning the house, laundry and care of clothing, shopping, repair and maintenance of dwellings, care of infants, children or adults, gardening, pet care, bookkeeping related to household management, and travel related to any of these activities (Zick, Bryant, & Srisukhumbowomchai, 2008). This analysis focused on people who are both in and out of the labor force. Both employed and nonemployed women were analyzed because housework is done, generally speaking, whether a woman is employed or not. The theoretical models that have been used to investigate housework time in the past were the bargaining model, feminist model, and household production model.

The bargaining model states that the allocation of time spent on housework depends on negotiations (bargaining process) that are made between household members (i.e., husband and wife, parents and child) and their relative bargaining power utilizing game-theoretic frameworks to analyze intrahousehold resource distributions (Lundberg & Pollak, 2007). The strength of each individual’s bargaining power is related to his or her next-best alternative, commonly referred to as the "threat point," and incorporates aspects such as differences in earnings when making decisions regarding time spent in housework (Hersch & Stratton, 1994; South & Spitze, 1994). Generally speaking, men have higher market wages than women; hence, men’s bargaining position in the home is likely to be stronger (Hersch & Stratton, 1994). As the bargaining model is applicable only to households with two or more members, it is not applicable for this analysis.

The feminist theory focuses on socialization and gender-role attitudes. This theory states that husbands and wives perform different tasks in the household based on previous knowledge and skills acquired, as well as what they believe is appropriate behavior for men and women (South & Spitze, 1994). This theory states that the allocation of housework is dependent on cultural norms that influence how much time a spouse will spend in the labor force versus time spent in domestic labor (Gough & Killewald, 2010). The feminist theory of household work does not apply to one-adult households because it is based on the relationship between men and women. For this reason, the feminist model is not an appropriate model to use for the analysis.

According to the household production model, households combine time and market goods via a production function to produce basic commodities where households allocate their time and money to maximize their utility, given a specific utility function (i.e., things that improve the individual’s well-being) and set of budget constraints. The standard household production model identifies three composite goods that provide satisfaction to households: goods and services purchased in the market (market goods: C), goods and services produced and consumed in the household (home goods: H), and leisure time of the individuals (L; Becker, 1965). The amount of each good consumed differs among individuals due to the factors that shape demand: nonwage income, net wealth, tastes and preferences, expectations, prices of goods and services, and wage rates. As an individual derives satisfaction from these three composite goods, the individual’s utility function can be described as a function of market goods, home goods, and leisure.

A household seeks to maximize utility subject to resource, legal, technical, and socio-cultural constraints on behavior, where these constraints are determined by conditions present both inside and outside the household (Bryant & Zick, 2006). Individuals are constrained by time (24 hours per day) and by the technology available with regards to household production (Bryant & Zick, 2006). Growth in capital and technology has improved the productivity of household activities (Ehrenberg, 2012). Another constraint the household faces is the budget constraint; changes in income have a two-fold effect on the household (through the income effect and substitution effect).

The household production function indicates the technological relationships involved in productive processes; it emphasizes the relationship between the time spent by an individual in household activities and the quantity of goods and service inputs with which the individual's household work time is combined. The household production function emphasizes that there is an input-output relationship: the input being time spent in household work activities and the output being the quantity of household goods produced. Mathematically, the standard form of the production function is given by $G = g(T_G, X_G; S)$ where T_G is the time input, X_G are the goods input, S is a vector of production technology shifters (e.g., BMI), and G is the quantity of household goods that are produced per day (Bryant & Zick, 2006). T_G and X_G are choice variables, whereas S is predetermined. In this model, the choices that individuals make regarding household time use decisions are hypothesized to be dependent on their preferences, nonwage income, wage rate, and predetermined productivity shifters (Ehrenberg, 2012).

Utilizing the household production model, household production (H) is a function of time spent in housework, amount of purchased goods used in household production, sociodemographic preferences, and BMI. Hence, the household production function is given by $H(T_H, X_H; BMI, D)$ where T_H is time spent in housework, X_H a vector of purchased goods used in household production, and D is a vector of sociodemographic production technology and/or preference shifters. Given that only a single day diary is used in this analysis, BMI and socio-demographic factors are viewed to be predetermined relative to the choice a woman is making about how to spend her time within one 24-hr period.

3.2.2 Utility Analysis

Individuals are utility-maximizers, which is to say, individuals want to maximize their level of well-being. Health, and with that one's BMI level, is one factor that contributes to people's utility, as individuals combine their time with market goods to improve, maintain, or ravage their health (Cawley, 2004). The underlying utility model used in this work is as follows:

$$U = u\,[L(T_L, X_L; BMI, D),\ H\,(T_H, X_H; BMI, D),\ BMI\,(T_B, X_B; D)]$$

Utility is derived from leisure production (L), household production (H), and BMI production (BMI). Leisure production is a function of time spent in leisure production (T_L), purchased goods used in leisure (X_L), and predetermined factors BMI and sociodemographic preferences (D); household production is a function of time spent in housework (T_H), purchased goods used in household production (X_H) and predetermined factors BMI and D; BMI is a function of time spent in BMI production (T_B) and purchased goods used in BMI production (X_B) and predetermined sociodemographic preferences.

The focus of this analysis is on the household production function [H (T_H, X_H; BMI, D)], which generates the derived demand equation for housework time. As noted earlier, in such a model BMI is posited to be predetermined. However, since BMI is simultaneously one of the choice characteristics in the utility function, it becomes questionable as to whether BMI is exogenous. Therefore, there is a need to test for the presence of endogeneity in the statistical analysis.

3.2.3 Hypothesis Testing: BMI and Housework

Household members have the choice of whether they want to provide the commodities themselves (i.e., conducting household work) or whether they would rather purchase the commodities in the market, subject to their income constraints. The degree to which this is influenced by one's BMI level, if at all, is the focus of this chapter.

The prediction regarding how overweight/obesity changes the demand for housework time is ambiguous.[6] If obesity is likely to cause less mobility in comparison to normal weight mobility, obese women will either spend more time doing housework because it takes them longer to do so, or obese women will spend less time doing housework if it is too strenuous; for example, and they may decide to purchase market substitutes instead.

[6] Another measure that relates to being overweight/obese besides BMI that could be used in the analysis is that of physically inactivity. Being physically active could lead to a more sedentary lifestyle and hence could influence the amount of household work performed. However, given the dataset, physically activity is not used as a measure for there are serious limitations with regard to the variable in the dataset.

The first hypothesis is that obese/overweight women spend more time, on average, on household work because it takes them longer to get the same amount of work done. This hypothesis agrees with the output differentials hypothesis: if nonobese individuals are more productive, then they would not have to spend as long doing housework in comparison to obese women. Thus, one would find the following relationship:

$$\frac{\partial housework}{\partial BMI} > 0 \quad \text{as BMI increases, time spent in housework increases}$$

What the above relationship indicates is that an individual who is obese may be less productive in each additional hour spent in household, in comparison to a normal weight counterpart. With this in mind, it may take an obese person longer to be as productive as a non-obese person. If this were to be observed, then the notion of diminishing marginal productivity would be a significant factor. Diminishing marginal productivity means that when one input to production is increased, *ceteris paribus*, the marginal product of that input falls (Bryant & Zick, 2006), which in this case means that the more time is spent in household activities, the less productive an additional amount of time is. Two common phenomena of diminishing marginal productivity are tiredness and congestion (Bryant & Zick, 2006). Given this, a potential reason why women with higher BMIs are less productive is because of fatigue.

The alternative hypothesis is that obesity/overweight may lead to less housework being done. Since individuals face a labor-leisure tradeoff, overweight/obese women could be spending less time on household work (labor) if they decide that leisure gives them higher utility. One of the potential reasons behind this is that when people gain weight, it becomes increasingly more difficult to move, thus causing a higher burden. Even though being physically active would ease that, it is sometimes difficult for obese/overweight people to be physically active. Hence, if weight gain causes physically activity to be burdensome, women may decrease the amount of time spent in housework and choose to do other activities instead, which would indicate the following relationship:

$$\frac{\partial housework}{\partial BMI} < 0 \quad \text{as BMI increases, time spent in housework decreases}$$

3.3 Methodology

3.3.1 Data

In order to analyze how (or if) obesity affects housework time, the most straightforward way of measuring such differences is an analysis of daily activities via BMI strata. Data for this chapter come from the public-use files of American Time Use Survey (ATUS), which collects time diary data on how Americans spend their time. ATUS respondents are interviewed about how they spent their time on the day preceding the interview, who they were with, and where they were. Hence, when analyzing the sample means, one is able to ascertain how an average day is spent and how, in general, people spend their time. This dataset has detailed descriptions of how individuals spend their time in both market and nonmarket work. The ATUS data include information on childcare and adult care, housework, volunteering, socializing, relaxing/leisure activities, exercising, and religious activities. In order to avoid biases in terms of what day the interview was conducted, half complete a diary for a weekday and half complete a diary for a weekend day.

ATUS respondents are drawn from households that have completed the Current Population Survey (CPS) in the preceding 2-5 months where a sample size of approximately 2000 households is randomly selected each month for interviewing (Letourneau & Zbikowski, 2008). Each ATUS respondent is randomly selected from household members who are age 15 and older living in a subset of households that have completed their 8th and final month of interviews for the CPS. Demographic information including sex, race, age, educational attainment, occupation, categorical household income, marital status, and the presence of children in the household is available for each respondent (ATUS, 2014). Households with minorities are oversampled in order to increase reliability about these subgroups of respondents (Letourneau & Zbikowski, 2008).

To capture how daily household productivity is potentially affected by an individual's BMI, the ATUS data were restricted for this analysis to the years 2006-2008, as those years include an additional module: the Eating and Health (EH) Module. The EH Module contains time-use questions on a range of eating and health topics such as time spent in eating and drinking activities, grocery shopping, and meal preparation and other self-rated health status questions. Critical to the current study, the module includes questions on height and weight that were used to compute BMI for each respondent, where BMI is calculated as weight (kg) / [height (m)]^2. One negative aspect of using this BMI measure is that the coefficients are prone to be biased due to measurement errors that occur from having self-reported rather than clinical measures of weight and height (Cawley, 2010). Although self-reported measures are not ideal, research has found self-reported weights are acceptable to use for nonelderly adults (Kuczmarski, Kuczmarksi, & Najjar, 2001).

The response rates for the ATUS EH Module are fairly high; only 5.5% are missing for the sample; 1% of missing responses is due to the respondents being pregnant (Hamrick, 2012). Total sample size for the EH Module for years 2006 to 2008 is 37,914 respondents. However, for both the nonmarket and market indirect costs analyses, the ATUS sample is restricted to female respondents who are between the ages of 25 and 64 and whose BMI ranges from 18.5 to 64. These age restrictions are imposed to capture those women who are most eligible for employment in the labor market (and not retired or in college/school) and also because a woman over the age of 25 is less likely to live with her parents than one who is younger.[7] Hence, by imposing the age restriction, those women who are not taking care of their own household are most likely to be excluded. In addition, since pregnancy affects a woman's weight, women were asked if they were pregnant and if they were, they were not asked their weight and thus their BMI is missing. Narrowing the dataset to just female respondents reduces the number of observations to 21,455 and eliminating those with exceptionally low or high BMI (i.e., not in the 18.5-64 BMI range) reduces the number of respondents to 19,127. Finally, imposing the age restrictions leads to a final sample of 13,323 individuals.

Since the data used for the study are survey data, sample weights are required for statistical analysis as those being sampled, generally speaking, often have different probabilities of being selected (Winship & Radbill, 1994). As the ATUS is based on a stratified random sample, ATUS responses are weighted so as to reduce bias in the

[7] It should be noted that one limitation to this study was that there is no variable in the ATUS dataset that would indicate whether the individual lives with their parents or not. Hence, if someone was over age 25 but living with parents, they are still in the sample, even though they should be excluded.

estimates that can result from differences in sample and response rates across subpopulations and days of the week (ATUS, 2014). For this reason, it is important to use sample weights as they ensure that each group and day is correctly represented for the population.

The ATUS provides specific sample weights for the EH Module, labeled EHWT, for which the weights are probability weights. The EH Module weights can be used with the corresponding set of replicate weights, labeled as REHWT in the ATUS dataset. Replicate weights are used in conjunction with sample weights in order to generate empirically derived standard errors for estimates they produce (ATUS, 2014) where standard errors are an estimated measure of the variation that is to be expected in the estimated value of a statistic across multiple samples drawn from a given population. Replicate weights are used in order to construct an estimate of the true standard error (Winship & Radbill, 1994).[8] Thus, when generating means for the population, replicate weights were used to calculate the correct standard error.

3.3.2 Descriptive Statistics

Weighted descriptive statistics are shown in Table 3.1. Average BMI for the sample is 27.45. Applying weights, close to 42% are of normal weight, 30% are overweight, and 28% are obese, where normal weight is defined as a BMI between 18.5 and 24.9, overweight is defined as a BMI between 25 and 29.9, and obesity is defined as a BMI greater or equal to 30 (Centers for Diseases Control and Prevention, Overweight and Obesity, 2012). Comparing the ATUS sample to national figures, national statistics

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[8] There are a total of 160 replicate weights for the EH Module. Thus, in order to calculate the standard errors for an estimate, one should generate 160 separate estimates using each of the 160 replicate weights (ATUS).

indicate that from 2003 to 2006, 36.6% of women were normal weight, 28.2% were overweight, and 35.2% were obese. These national statistics, however, are for all women and thus are not directly comparable to the ATUS subsample used here. In comparison to national statistics, the ATUS sample has a greater percentage of the population that is of normal weight. Though national figures are not available for 2006-2008, it seems unlikely that the differences are attributable to the differences in the years in which the data were gathered. If individuals are misclassified because of systematic self-reporting errors, this would lead to a conservative bias for the study.

The average age of women in the sample is 44.23, and 85% are in good health (given by fair, good, or very good health status). Approximately 64% are married, 13% are divorced, and 16% have never married. Analyzing the number of children in the household, 53% have no children living in the home, 19 % have 1 child, 18% have 2 children, and close to 10% have three or more children. Seventeen percent of women have some college but no degree, 11% have an associate degree, and 33% have a bachelor's degree or higher level of education. In total, close to 61% have more than a high school degree and approximately 39% of women have a high school degree or less.

The majority of the women are employed (75%), 20% have an annual family income of less than $30,000, 27% have a family income between $30,000 and $60,000, 33% have a family income between $60,000 and $150,000, and 7% have an annual family income of $150,000 or more. With regard to weekly earnings, approximately 40% have weekly earnings between 0 and $499, 38% between $500 and $999, 14% between $1000 and $1499, 5% between $1500 and $1999, and less than 4% earn $2000 per week or more. Measuring poverty status, 72% of women had household income that was greater than 185% of the poverty threshold.

The mean time spent in total housework for all women is 188 minutes per day; analyzing this by BMI category, normal weight women spend 196 minutes per day (208 minutes when including travel time), overweight women spend 186 minutes per day (196 minutes when including travel time), and obese women 176 minutes per day (185 minutes when including travel time), on average. Analysis of variance (ANOVA) indicated that these mean differences by BMI strata are statistically significant for both total time spent in housework, with or without including travel-related time.

The variable *total_housework* is a composite of the following housework activities: housework (which includes interior cleaning, laundry, sewing, repairing and maintaining textiles, and storing interior household items, including food); food and drink preparation (which includes presentation and kitchen and food clean-up); interior maintenance, repair, and decoration (which includes interior arrangement, building and repairing furniture, and heating and cooling); exterior maintenance, repair, and decoration (which includes exterior cleaning); household management (which includes financial management, household and personal organization and planning, household and personal mail and messages, household security, and household and personal e-mail); and time spent taking care of children. Also included is taking care of one's lawn, garden, and houseplants and housework time related to taking care of animals and/or pets.

Separate analyses were performed in order to include travel time in the analysis, specifically referring to travel time related to household activities. This dependent variable is labeled *total_housework _travel*, which correlates to the housework variable noted above. Only primary activities, which measures an individual's main activity where simultaneous activities performed are not included (BLS, 2014), are used to measure total household productivity as including all simultaneous activities (i.e., secondary activities) would lead to time spent on all activities to exceed 24 hours of a day (Chadeau, 1992).

3.3.3 Covariates

The household production function is given by G = g (H; X) where H are the hours of labor used per day and X are other inputs available. The number of household goods that are produced per day (G) is thus directly dependent on H and X, which themselves are directly dependent on other factors. Hours of labor used, as discussed above, are dependent on how individuals spend their day: market work, housework, or leisure activities. These activities are shaped by preferences (which cannot be measured directly), wage rates and nonlabor income. Hours of labor and output produced are also determined by marginal productivities of the individual, which in turn are a function of the technical relationship between inputs and output, as well as the capital used in the production.

Covariates used in the regression analysis should include factors, in addition to BMI, which are hypothesized to affect preferences, technical parameters of the production function, and wage rates and nonwage income. Covariates used in the regression analysis include age, general health status, education level, employment status, marital status, family composition (number of household members, number of children), day of the week, type of day (holiday or not), and race/ethnicity. These covariates were used in the regression analysis as the literature has found that these factors influence housework time, through influencing preferences or household production parameters

(Bianchi & Milkie, 2010; Bianchi, Milkie, Sayer, & Robinson, 2000).

The statistical analysis controlled for the day of the week that the interview took place, as interviews can be conducted on weekend, weekdays, and holidays, all of which affect time spent in housework for they alter preferences for time use or production technology. The respondents' diary day was randomly selected where 50% came from weekends and 50% came from weekdays. A new variable that indicated whether it was a weekday (Monday-Friday) or weekend (Saturday and Sunday) was created. The dummy variable created for measuring day of week was DAY_CAT where DAY_CAT = 0 indicates that it was a weekend and DAY_CAT = 1 indicates that it was a weekday. A dummy variable was created in order to control for whether the diary day took place on a holiday or not; HOLIDAY = 1 indicates that it was a holiday and HOLIDAY = 0 indicates that it was not a holiday.

Race/ethnicity is another factor that determines time spent in housework, as research suggests that time spent in housework differs among groups (Wight, Bianchi, & Hunt, 2012); this is potentially due to cultural or preferential differences. Though the analysis controls for race/ethnicity, Chapter 4 will delve further into race and ethnicity factors. In the analysis, RACE_CAT = 1 represents non-Hispanic White and RACE_CAT = 0 represents if race other than non-Hispanic White.

Household composition (e.g., number of children, number of household members, and marital status) has a direct effect as to how much time is spent on housework. Being married increases time spent on housework for women, while most studies report little or no difference for men (Bianchi, Milkie, Sayer, & Robinson, 2000). Marital status is measured via six categories in the ATUS dataset: "married - spouse present"; "married -

spouse absent"; "widowed"; "divorced"; "separated"; and "never married." The data were transformed to include those who are married versus those who are not married (which included never married, widowed, and divorced). Given that this dataset stemmed from the ATUS-X data, an individual is classified as single even if she was cohabitating. For the analysis, MARST_CAT = 1 indicated married and MARST_CAT = 0 indicated never married, widowed, or divorced.

Children cause their mothers to transfer time from market to home tasks as the number of children is positively related to time spent in housework (Bianchi et al., 2010). It has been established that women with very young children spend more time in housework and decreased time in market work; these disparities shrink with older children (Bryant & Zick, 2006). Hence, the number of children is a significant cofactor to use with regard to factors influencing household work. The variable for number of household children (HH_NUMKIDS) was utilized in the regression analysis in order to capture the effect of having children; in the ATUS dataset, the number of children per household ranged from 0 to 12. Given that age of child matters, KID1TO2 was used in the regression, which accounts for whether a respondent has an own child between the ages of 1 and 2 living in the household.

The variable that defines the type of living quarters (HOUSETYPE) was defined as living in "house, apartment, or flat" or otherwise (e.g., nontransient/transient hotel or motel, rooming house, mobile home, or student quarters in college dorm). Over 95% of the respondents answered that they lived in the house, apartment, or flat category. For this reason, a new dummy variable was created (HOUSETYPE_CAT) where house type equal to1 applies to "house, apartment, or flat" and 0 for all other housing types.

General health status is another potential cofactor to be incorporated in this analysis because if one's health is poor, one may not be able to function as well as a healthy individual; hence, health could have a negative impact on total housework performed. General health status is measured on a scale from 1 to 5 in the ATUS dataset where 1 is excellent (health), 2 is very good, 3 is good, 4 is fair, and 5 is poor; 97 respondents answered the questions with "don't know" and hence were excluded from the analysis. General health status was categorized as either good health (includes excellent, very good, and good) or poor health (includes fair and poor). The dummy created for this was GENHEALTH_CAT where GENHEALTH_CAT = 1 refers to good health and GENHEALTH_CAT = 0 refers to poor health. Interestingly, even though a high percentage of women in this sample are overweight/obese, 85% of women categorize themselves as in good health and 15% categorize themselves as in poor health.

Several categories were associated with the education variables from less than 1st grade to profession school degree. The majority of the participants were high school graduates with diploma (26.51%), followed by those with a bachelor's degree (22.21%), and then those with some college but no degree (17.41%). The dummy variable created to capture the effects of education was whether or not the individual's educational level was greater or less than a high school degree. The categorical dummy variable EDUC_CAT was created to capture this; EDUC_CAT equal to 0 means less than or equal to a high school degree (including GED) and EDUC_CAT equals 1 refers to more than a high school degree. In the sample, 34% of women had a high school degree or less, whereas 65% of women had more than a high school degree.

Income should be incorporated into the regression analysis, but, given the nature of the data, no inherently accurate measure of woman's income is available *per se*. There is no "nonwage" income variable, which would have been the most appropriate variable to incorporate in the model, as it would capture a wage for those in and out of the labor force. There is "family income," which would not be a direct reflection of the woman's earning as it takes into account all earnings for family members.

Another potential variable that could have been used to measure a woman's income is weekly earnings. One of the problems associated with using weekly earnings as a measure of income is that it has the potential of being endogenous with time spent in housework; hence, weekly earnings were not used. Instead, the analysis focused on employment status, which is predetermined when viewed in the context of a single 24-hour diary day. Other economic measures pertaining to income, such as family income or poverty line measures, were used for those economic measures that provide the most confidence that they are not endogenous variables. The categorical variable used to measure if household income is less than or equal to 185% of poverty threshold or whether income is greater than 185% of poverty threshold is labeled POVERTY.

Given these factors, along with BMI, that influence time spent in housework, the theoretical model was given by:

> Household activity ($\sum$daily activities) = *function of* (BMI, education, number of children/number of members in the household, age, race, labor force status, general health status, marital status, type of household, poverty status, young children or not).

3.4 Regression Analysis

For this empirical investigation, the primary focus was to determine whether BMI has an impact on household productivity, while taking other theoretically guided covariates into account. The dependent variable for the model was total housework time, so that the relationship between changes in BMI and housework time could be analyzed. The main hypothesis to be tested was whether BMI has a significant impact on housework, thus the null hypothesis for the study is H_0: $\beta_1 = 0$. The analysis focused on whether the relationship between BMI and housework is positive or negative.[9]

3.4.1 Regression Equation

Before constructing the correct functional form for the regression analysis, correlation and functional form were tested for by analyzing scatter plots. Whether BMI is a linear function of time spent in housework or a nonlinear function was tested. After analyzing the relationships between the BMI and total time spent in housework, a linear relationship was found. The full form for the regression models is given as:

Regression Model I:

$$\textbf{total\_housework} = \beta_0 + \beta_1 BMI + \beta_2 AGE + \beta_3 MARST\_CAT\_D + \beta_4 EDUC\_CAT\_D + \beta_5 DAY\_CAT + \beta_6 HH\_NUMKIDS + \beta_7 HOUSETYPE\_CAT + \beta_8 RACE\_CAT + \beta_9 TENURE\_CAT + \beta_{10} GENHEALTH\_CAT + \beta_{11} POVERTY + \beta_{12} KID1TO2 + \beta_{13} HOLIDAY + \beta_{14} EMPSTAT\_CAT + \varepsilon$$

Regression Model II:

$$\textbf{total\_housework\_travel} = \beta_0 + \beta_1 BMI + \beta_2 AGE + \beta_3 MARST\_CAT\_D + \beta_4 EDUC\_CAT\_D + \beta_5 DAY\_CAT + \beta_6 HH\_NUMKIDS + \beta_7 HOUSETYPE\_CAT + \beta_8 RACE\_CAT + \beta_9 TENURE\_CAT + \beta_{10} GENHEALTH\_CAT + \beta_{11} POVERTY + \beta_{12} KID1TO2 + \beta_{13} HOLIDAY + \beta_{14} EMPSTAT\_CAT + \varepsilon$$

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[9] The statistical program used to run all analyses was SAS 9.2. Two-stage least squares analyses were done using proc syslin data = test 2SLS.

Even though it would be preferential to use longitudinal data to analyze the effect that BMI potentially has on time spent in housework, no such data exist concerning time use. When using cross-sectional data for the regression analysis, potential data problems may arise. One such problem is that since the data are collected on one particular day, the data may not reflect how an individual behaves usually, so measurement errors may arise. Omitted variable bias may also occur if there are unobserved factors that affect BMI and housework that are not accounted for.

Multicollinearity arises when independent variables are highly, but not perfectly, correlated. When multicollinearity arises, though the regression model retains all its assumed properties, the problem is that the regression coefficients have large standard errors thus meaning that the coefficient cannot be estimated precisely (Gujarati, 2002). Multicollinearity affects the outcomes as the t-statistic value is underestimated (Ajmani, 2011). If multicollinearity were present, it would be wise to either obtain more data though the more "practical" remedy is to drop variables suspected of causing multicollinearity in the regression analysis (Greene, 2002).

Checking a model for the presence of multicollinearity can be done through testing the variance inflation factors (VIF), condition indices, and proportion of variation associated with each parameter estimator (Ajmani, 2009). The independent variables that are used, and tested, in this regression are BMI; age; education level; number of children; marital status; general health status; race; whether living quarters were owned, rented, or occupied without rent (TENURE_CAT); and whether the interview day was a holiday. Here the variables that are categorical are education, marital status, general health status, living quarters, and holiday. The key to reducing multicollinearity in regard to dummy variables is to choose the correct reference category (Wißmann et al., 2007); in order to reduce high VIFs, one should choose the reference category with the larger portion of observations. Though there are not any set rules associated with testing for multicollinearity, the general rule of thumb for detecting problematic multicollinearity is a condition index over 5 and two proportion of variation figures greater than 0.5 (Belsley, Kuh, & Welsch, 2004).

After testing for multicollinearity, results showed potential multicollinearity for BMI and age, and when including the categorical variable house type. As such, age was recategorized from a continuous variable to a categorical variable; the age category that was created was whether the woman was in child bearing years (less than or equal to 45 years of age) or not (greater or equal to 45 years of age). After adjusting for age and not utilizing type of house, there are no issues with multicollinearity for this statistical analysis (Appendix A).

Given that BMI is an independent variable and household production time is the dependent variable, when using BMI as a right side variable in the statistical analysis, there is the possibility of reverse causality arising. A causal association from housework to BMI would create endogeneity issues. There is potential that high BMI causes a woman to spend less time in housework or, on the other hand, less housework time could lead to higher BMI.

Identification of the preferred model for the regression analysis, that is whether to use ordinary least squares estimation (OLS) or two-stage least squares (2SLS), required testing for endogeneity using the Hausman specification test. If endogeneity was present, instruments had to be identified to conduct 2SLS estimation; after instruments were identified, strength of those instruments was tested, and then the independence of the instruments was tested (Zick, Stevens, & Bryant, 2011).[10] This will be discussed in subsequent sections.

It should be noted, however, that there are potential problems when using 2SLS estimation instead of OLS estimations, specifically in regard to the instruments used in 2SLS. Instruments have the potential to be flawed during the estimation procedure if it is correlated with the disturbance term, hence it is an invalid instrument, or when an instrument is weakly correlated with the endogenous variable (Murray, 2006). As noted by Murray (2006), strength of the instruments can be tested for all instruments suffer from the possibility of being invalid.

The first step in assessing the simultaneity of BMI and time use is to calculate the Hausman F-test statistic to establish whether there was a correlation between the regressor and the error term (Griffiths, 1993). The Hausman specification test identifies the preferred model by analyzing for the existence of endogeneity in the model; testing for the presence of endogeneity in a model is important for if it is present, the method of least squares cannot be applied because the estimators obtained are inconsistent (Gujarati, 2002). Another reason it is important to first test for endogeneity is that if we were to use the alternative method of two-stage least squares and in fact that was no simultaneity present, the estimators would be consistent but not efficient (Gujarati, 2002).

[10] In the 2006-2008 sample, 1740 (12.82%) of the sample reported doing 0 minutes of housework. If a sizable number of individuals report doing no housework, the estimates could be skewed and one would have to use a Tobit analysis. Given the number of individuals who responded with 0, it seems unlikely that a Tobit analysis has to be performed.

3.4.2 Hausman Test

Under the null hypothesis of the Hausman test, there is no simultaneity and one would use an ordinary least square regression for the analysis. If there are no simultaneity issues (i.e., BMI and total_housework are mutually independent), BMI and ε should be uncorrelated. When using the Hausman specification test, the following hypothesis is tested: H_0: BMI is exogenous versus H_1: BMI is endogenous. If the t-statistic corresponding to μ(hat) is significant, then the null hypothesis is rejected and BMI is endogenous. The results show a t-value of 3.91 (*p*-value = <0.0001), which is statistically significant. Therefore, the model indicates that BMI is an endogenous variable.

As endogeneity is confirmed in the model, instruments were identified and tested for strength and independence. In order to find valid instruments for this model, a variable should be correlated with BMI, conditional on the other variables that affect household production, and also at least one variable that was correlated with BMI but unrelated to the error term in the time use equation (Cawley, 2010). Instruments are used as a proxy for the endogenous variable; hence the goal is to find a proxy that is highly correlated with BMI, in this case, but uncorrelated with the error term (Gujarati, 2002). The greater the correlation is between the random regressor and the instrument, the more efficient the instrumental variable estimator is (Griffiths, 1993).

3.4.3 Instruments

Instruments should be correlated with the endogenous variable (BMI) but be uncorrelated with the dependent variable (time spent in housework). Instruments that have been used for BMI are area-based measures, such as urban versus rural location or region (e.g., South or West; Currie, & Cole, 1993). The instrumental variable reflecting area-based measures for this analysis is region. Region is a categorical variable, which was transformed into dummy variables. Region equal to 1 pertained to Northeast, region equal to 2 to Midwest, region equal to 3 to South, and region equal to 4 to West.[11] Given this, the dummy variable that was created for region (region_cat_d) singled out the region with the highest BMI, which is the South, according to the Centers for Disease Control and Prevention. Singling out the South allows for creating an instrument that is correlated with BMI and not with housework. Hence if region equaled 3, region_cat_d equaled 1 and if region did not equal 3, region_cat_d equaled 0.

Other instruments that were used in the model were whether the diary day came from 2006 and whether the woman participates in a food stamp program, which was measured by whether a household received food stamps in the past 30 days. Whether the diary day came from 2006 was used as an instrument as BMI levels have been changing through the years, while time spent in housework has been relatively consistent; according to the BLS (2014), on average, women's time spent in housework in 2006 was 2.23 hours per day, 2.22 hours per day in 2007, and 2.13 hours per day in 2008. Food stamp participation was used as an instrument as it is likely, according to studies, to influence BMI level while food stamp participation is not hypothesized to be related to time spent in housework.

Even though it is not possible to say whether an instrumental variable estimator is efficient (Griffiths, 1993), the more correlation that exists between the instrument and the random regressor, the more efficient the instrument is. In general, there are two

[11] When using all four region categories (region_cat_1, region_cat_2, region_cat_3, region_cat_4) and dropping one of the categories as the instruments for the regression analysis, the test for overidentification failed. Hence, one dummy category was created for region (region_cat_d).

requirements for an instrument: the first is that the instrument must be powerful and the second is validity (Cawley, 2010). There are several ways to decipher the strength of an instrument; one is to calculate Hansen's J-statistic in order to test the independence of the instruments from the error term (Zick et al., 2007). Weak instruments occur when the selected instrumental variable used has a poor correlation with the endogenous variable (Ajmani, 2011). The test for weak instruments is based on the Cragg-Donald statistics where the null hypothesis is that the instruments are weak and the alternative is that they are not (Stock & Yogo, 2003). In order to test the existence of weak instrument, a rule of thumb (the Staiger-Stock rule of thumb) proposed in the literature is that the weak instruments problem is a nonissue if the F statistic of the regression in the reduced form equation exceeds 10 (Ajmani, 2011), as instruments are considered weak if the first-stage F-statistic is less than 10 (Stock et al., 2003). It should be noted, however, that this rule of thumb does not hold as strongly when the number of instruments is moderate or large due to the fact that the critical value is much larger (Stock et al., 2003). The reduced form parameters are estimated by OLS regression. For the BMI equation, the F-statistic is 89.07, and thus larger than 10. Therefore, given the Staiger-Stock rule of thumb, the null hypothesis of weak instruments is rejected.

To test for an instrument's validity, overidentification was tested for, as it determines whether model has more instruments than are necessary (Baum et al., 2003). Hence, what the test for overidentification examines is whether added instruments to the model are exogenous (Wooldridge, 2002). The test for overidentification requires Sargan's hypothesis test. To perform Sargan's hypothesis test is to run a 2SLS to obtain the residual(hat) term and then regress (via OLS) this residual(hat) variable on the instruments. Sargan's test statistic is then tested by analyzing nR^2 (Wooldridge, 2002). Sargan's test statistic is a special case of Hansen's J-test under the assumption of conditional homoscedasticity (Baum et al., 2003).

Under the null hypothesis of exogenous extra instruments, the test statistic is distributed as a Chi-squared random variable. If the null hypothesis is rejected, then the instrument used in the regression needs to be reexamined. Using Sargan's test, one obtains the residual(hat) term. To test whether or not extra instruments are exogenous and an overidentified model can be used, the residual(hat) term is regressed on all the instrumental variables. In order to verify whether or not this overidentified model can be used, the nR^2 obtained from the model is compared with the critical value. If the test-statistic (nR^2) is greater than the critical value, then the null hypothesis is rejected and the regression needs to be reexamined.

From the regression analysis, the R^2 value equals 0.0001 and the number of observations in this regression equals 13,094; hence nR^2 equals 1.309. The critical value (Chi-squared value) is 3.84 (at the 5% level) for 1 degree of freedom. Therefore, the test-statistic value is smaller than the critical value and the null hypothesis is not rejected. For this reason, it is valid to use additional instruments.

3.5 Regression Results

When using 2SLS and the instrumental variable technique, the following models were tested (one to include travel time and one to exclude it); the model now accounts for changes made due to the presence of multicollinearity (categorical age variable and exclusion of house type):

Model I:

$\boldsymbol{total\_housework} = \beta_{0} + \beta_1 BMI + \beta_2 AGE\_CAT + \beta_3 DAY\_CAT + \beta_4 EMPSTAT\_CAT + \beta_5 EDUC\_CAT\_D + \beta_6 MARST\_CAT\_D + \beta_7 GENHEALTH\_CAT + \beta_8 HH\_NUMKIDS + \beta_9 HOLIDAY + \beta_{10} RACE\_CAT + \beta_{11} TENURE\_CAT + \beta_{12} POVERTY + \beta_{13} KID1TO2 + \mu$

Model II:

$\boldsymbol{total\_housework\_travel} = \beta_{0} + \beta_1 BMI + \beta_2 AGE\_CAT + \beta_3 DAY\_CAT + \beta_4 EMPSTAT\_CAT + \beta_5 EDUC\_CAT\_D + \beta_6 MARST\_CAT\_D + \beta_7 GENHEALTH\_CAT + \beta_8 HH\_NUMKIDS + \beta_9 HOLIDAY + \beta_{10} RACE\_CAT + \beta_{11} TENURE\_CAT + \beta_{12} POVERTY + \beta_{13} KID1TO2 + \mu$

After running the regressions, Model I indicates that BMI is statistically significant (*t*-value: -4.13 and *p*-value <0.0001), with a coefficient of -6.64 indicating that for the overall sample, as BMI increases, time spent in housework decreases. The coefficient on BMI for Model II (total_housework _travel as dependent variable) is also statistically significant (*t*-value of -3.08 and *p*-value <0.0001) and a coefficient of -5.06. In Model I other statistically significant variables were day of week, employment status, marital status, number of children, whether it was a holiday, general health status, race, and poverty line status (Table 3.2 and Table 3.3).[12] The results for the coefficients associated with the covariates are consistent with what has been shown in the literature in the past.

As the goal is to ascertain whether being overweight and/or obese affects the amount of time spent in housework, BMI was categorized and then analyzed via the framework as before. There are categorical variables for normal weight, overweight, and obese. When running the regressions, the statistical approach used was to omit the normal weight category so as to analyze the results obtained from the overweight and obese

[12] The results regarding which variables were statistically significant were the same for Model II as they were for Model I with the exception of the holiday variable, which was not statistically significant in Model II.

categories, in comparison to normal weight women.

For Model I, the regression results indicate that overweight women, in comparison to normal weight women, spend 6.17 minutes less on housework time per day while obese women, in comparison to normal weight women, spend 14.52 minutes less on housework per day (both variables are statistically significant). When including travel-time related to housework (Model II), again both variables are statistically significant and results show that overweight women spend 6.37 minutes less per day on housework and obese women spend 15.23 minutes less on housework per day, in comparison to normal weight women (Tables 3.4 and 3.5).

When analyzing the differences between total time spent in housework (including travel time), the annual differences in housework for each group are substantial. These differences in less time spent on housework per day translate into approximately 39 hours less time spent on housework for overweight women, in comparison to normal weight women, per year and approximately 93 hours less time spent in housework for obese women, per year. If one were to value this time at the median hourly wage for a housekeeper, where the 2008 median hourly wage for a housekeeper was $9.13 (BLS, 2008), the total cost per year for overweight women is approximately $354 and approximately $846 for obese women measured in 2008 dollars.

3.6. Market Costs of Overweight/Obesity

From the above analysis, results indicated that indirect costs of household production of obesity are substantial but the question remains as to whether there are also occupational costs. Specifically, is there an implicit occupational penalty for being overweight or obese? In order to test this proposition, occupations were ranked to see whether or not a relationship exists in terms of occupation and BMI. In order to rank occupations, the occupational socioeconomic scores were used as they reflect both the average education and income of the occupation and hence are ranked via those criteria; these scores then represent a level of living for the typical person in specific job classifications (Nam & Boyd, 2004). Such occupational prestige scores are proxies for social class. There are different prestige-based rankings of occupation, such as Siegel's scale, the Duncan scale, and the Nam-Powers-Boyd scale. The difference between these three scales is that the first is based on a pure prestige scale, the second on a socioeconomically predicted prestige scale, and the third on a pure socioeconomic scale (Nam & Boyd, 2004). The Nam-Powers-Boyd occupational prestige scores are based on a scale from 0 to 100 where 0 indicates the lowest possible score and 100 the highest; survey questions address education, income, and age of the participants.

The 2000 Nam-Powers-Boyd Occupational Status Scores (OSS) are computed by equally weighting earnings and education for those in the civilian labor force, ages 16 and above. The occupational scores are based on the individual's primary occupation and hence negate any secondary work activity. The highest score (100) on the Nam-Powers-Boyd scale is for dentists, physicians, and surgeons, whereas the lowest score is that for counter attendants in cafeterias, food concessions, and coffee shops and for dishwashers. It is interesting to note that occupational status scores have been shown to vary distinctively among social groups as there is a gradient in status among different groups in the American society; these groups are defined by sex, age, location, race and ethnicity (Nam & Boyd, 2004). However, the correlation between occupational prestige and BMI has not been tested.

3.7. Market Analysis

For this analysis, only women who were employed were included in the sample. Occupations were grouped in accordance with the Nam-Powers-Boyd scale where the thresholds were ascertained from the scale itself. The Nam-Powers-Boyd scale ranks occupations on a scale from 1 to 100 where 1 indicates the worst occupation and 100 the best occupation. From this scale the occupations were grouped into 10 different categories; the categories represent the top 10%, top 20% and so forth (Table 3.6). Using the ATUS EH 2006-2008 data, 9566 women were observed to be in 1 of the 10 categories; approximately 60% of the sample hold occupations in the top 1-5 categories (Table 3.6).[13]

As occupation is determined in large part by educational attainment, this was measured by the following categories: more than high school degree attained or high school degree of education, or less. From the overall sample, 29.53% of the women have a high school degree or less and 70.47% of the women have more than a high school degree. When analyzing top 50% of occupations (occupation categories 1-5) versus bottom 50% of occupations (occupation categories 6-10), the difference that education makes was apparent. Of those women in the top occupations (groups 1-5), 85% of women had more than a high school degree; for those women in lower occupational ranking groups (groups 6-10), only 38% of the women had a high school degree or more (Table 3.7).

Analyzing the potential correlation between BMI and occupational status, several

[13] All the statistics presented in this section are weighted.

observations can be made. First, from the group of women for which data on occupation is available, 4252 are normal weight (44%), 2817 are overweight (30%), and 2497 are obese (26%). Those who are in top occupations (groups 1-5), 2,758 are normal weight, 1,608 are overweight, and 1,320 are obese, for those who are in bottom occupations, 1,494 are normal weight, 1,209 are overweight, and 1,177 are obese (Table 3.8). Analyzing the women in the top occupations (groups 1-5), approximately 48% are normal weight, 29% are overweight and 23% are obese, whereas for women in lower occupations (groups 6-10), approximately 39% are normal weight, 31% are overweight, and 30% are obese (Table 3.8). Hence, solely based on BMI, the observation can be made that there is a higher percentage of normal weight women in top occupations than in bottom occupations, whereas there is a higher percentage of women who are overweight and obese in lower occupations than in higher-ranked occupations.

Analyzing occupational categories when taking education levels into account shows that for those women with less or equal to a high degree of education and in top occupational categories (groups 1-5), 37% are normal weight, 32% are overweight and 31% are obese, whereas in bottom occupational categories (groups 6-10), 34% are normal weight, 33% are overweight, and 33% are obese (Table 3.9). For those women who have more than a high school degree, the distribution for the top occupations (groups 1-5) is as follows: approximately 51% are normal weight, 28% are overweight, and 22% are obese; for this group of women, analyzing the bottom occupations (groups 6-10), 43% are normal weight, 29% are overweight, and 28% are obese (Table 3.10). Chi-square values were calculated for each table to test for statistically significant differences in the column percentages; for those with less than a high school degree the Chi-square value was not statistically significant while for those with more than a high school degree is statistically significant. Hence, there were observed differences among the groups for those with more than a high school degree.

The data show that for those who were in top occupations, 79% were non-Hispanic White women, 10% were non-Hispanic Black women, 4% were non-Hispanic Asian women, and 6.5% were Hispanic women. Analyzing those who were in the bottom occupations, 63% were non-Hispanic White, 16% were non-Hispanic Black, 4% were non-Hispanic Asian, and 17% were Hispanic women. Taking education into account, the analysis was extended to include differences by racial/ethnic group and BMI level. For those who have more than a high school degree and who have top occupations, the following observations were made: for non-Hispanic White women, 53% are normal weight, 27% are overweight, and 20% are obese; for non-Hispanic Black women, 25% are normal weight, 35% are overweight, and 39% are obese; for non-Hispanic Asian women, 74% are normal weight, 21% are overweight, and 5% are obese; for Hispanic women, 51% are normal weight, 25% are overweight, and 23% are obese. Thus, for all racial/ethnic groups but non-Hispanic Black women, it was observed that having a high school degree or more and having a top-ranked occupation is correlated with higher rates of normal weight women, in comparison to overweight or obese women (Table 3.11). [14] The Chi-square value was statistically significant, hence there were observed differences between the groups.

For those women who have lower ranked occupations and a high school degree or less, the following observations were made: for non-Hispanic White women, 39% were

[14] For the total group of women who had higher-ranked occupations but a high school education or less, 37% were normal weight, 32% were overweight, and 31% were obese.

normal weight, 32% were overweight, and 29% were obese; for non-Hispanic Black women, 21% were normal weight, 34% were overweight, and 45% were obese; for non-Hispanic Asian women, 75% were normal weight, 20% were overweight, and 5% were obese (though sample size is quite small for this particular group); for Hispanic women, 28% are normal weight, 36% are overweight, and 35% are obese. Disregarding non-Hispanic Asian women, due to sample size, the observation of BMI relating to occupation is not as strong as that regarding top occupations (Table 3.12). The observed differences between the groups are statistically significant, as computed by the Chi-square value.

3.8 Discussion

From the analyses conducted in this chapter, insights were provided regarding both nonmarket and market penalties of being overweight and obese. Analyzing nonmarket attributes of overweight and obesity, this study concluded that being overweight or obese significantly reduces time spent in housework activities, in comparison to their normal-weight counterparts.

Overweight women, on average, spend 6.17 minutes per day less on housework work (not including time related to household activities) and 6.37 minutes per day less when including travel time; per year this would equate to approximately 37.53 hours less on housework when not including travel time, and 38.75 hours when including travel time. Obese women were shown to spend 14.52 minutes less on housework, in comparison to their normal-weight counterparts, when not including travel time and 15.23 minutes less on housework per day when including travel time; per year this indicates that obese women spend approximately 88.33 hours less on housework (not including travel time) and 92.65 hours when including travel time.

These results indicated that overall economic costs of obesity, as described in the literature, are conservative estimates for they do not take these additional indirect costs into account. It is apparent that being overweight or obese adds to indirect costs for there are significant reductions in time spent in household activities. Valuing this time at the median hourly wage for a housekeeper in 2008, the total cost per year for overweight women is $354 and $846 obese women.

The annual medical cost of obesity in the United States, in 2008 dollars, was estimated to be around $147 billion (CDC, 2014); if one were to include the indirect costs, as ascertained by lost household productivity, it would account for additional billions being spent on the obesity epidemic. The female population in the United States in 2009 between the ages of 25 and 64 is approximately 104 million women; given that 36.4% of the female population in 2009 was obese, this translates into approximately 38 million obese women and given that 28.3% of the female population was overweight in 2009, approximately 29.5 million women were overweight. Thus, the per person annual amount (e.g., $354 per overweight woman and $846 per obese woman) translate into the following annual costs: over $10 billion for overweight women and over $32 billion for obese women.

Though a direct comparison could not be made as to whether the housework penalty is higher than the wage penalty, an initial assessment was made based on Cawley's study. The study concluded that non-Hispanic White women face the highest wage-penalties as an increase of two-standard deviations from the mean caused a 9%

decrease in wages (4.7% decrease for non-Hispanic Black and 6.8% decrease for Hispanic females). Median annual earnings for full-time women in the United States are estimated to be around $39,157 (BLS, 2013); given this, the wage penalty would amount to approximately $3525 per year for obese non-Hispanic women, $1840 for obese non-Hispanic Black women, and $2663 for Hispanic women. As housework penalty costs are $846 per obese woman per year, they are speculated to be less than the wage penalties, but still significant.

From the regression analysis, the results show that “race” is statistically significant; being White leads to spending approximately 16 minutes more on housework per day than being non-White (this indicates that White women spend, per year, approximately 97 hours more on housework than non-Whites). Given that obesity risk is related to race/ethnicity and housework time varies by race/ethnicity, then the question arises whether it is not race/ethnicity *per se* that leads to differences in housework, but rather if it stems from obesity. This is the motivation for Chapter 4: are historical estimates of housework differences attributed to race/ethnicity a function of obesity status instead?

Analyzing the impact that BMI has on occupational status, the insights drawn from this study indicate that the impact of BMI and occupational status is more apparent for those with higher educational attainment and those with higher-ranked occupations. For those with a high school degree or less, the percentage of women who are normal weight, overweight, and obese in top and bottom occupations is close to equal (Figure 3.1). However, for those women who have a high school degree or more, for those in top occupations, there is a much higher percent of normal weight women than overweight or obese women; similar results can be seen for those in bottom occupations for those with more than a high school degree, however, in top occupations the percent of normal weight women far outweigh the percent of women who are overweight and obese, whereas in bottom occupations the degree to which the percent of women who are normal weight is higher than those who overweight and obese is only slight (Figure 3.2).

Therefore, for those with less educational attainment BMI stratification is less likely to be a factor with regard to occupational status as the percent in each category is practically equal. However, for those women with more educational attainment and in top occupations, there are defined gradients between BMI strata: the percent of normal weight is greater than the percent of overweight and obese women. Thus, there may be some degree to which occupational status is correlated to BMI strata. The Chi-square values were statistically significant for those with more than a high school degree, hence there is observed differences between the groups.

There were certain limitations that were faced during this study. First, there were data limitations. Given the nature of the data (i.e., survey data), all measures were self-reported. Most importantly, BMI is a self-reported measure. Thus, the results are likely to have a conservative bias with regards to housework analysis and occupational costs because of under-reporting of weight by women, which would lead to a misclassification of some women as normal weight when in fact they are overweight or obese. Also, time spent in housework may be imperfectly measured as the analysis was limited to one diary day. Hence, if an individual did not do any housework that day, it would be counted as 0 minutes; though included in the analysis, this may not be an accurate reflection of a woman’s normal household activity. Questions regarding average housework per day or week would have been more valid (but perhaps less reliable) for this analysis. Another limitation that is faced is that the analysis cannot test for whether another member of the household, or outside the household, is contributing to housework. This could lead to either liberal or conservative estimates; if normal weight women are more likely to have other members contribute to household work, the results are liberal for not taking this into account. On the other hand, if overweight or obese women are more likely to have others contribute to housework, the results are conservative.

Given that a wage penalty was observed for both overweight and obese women, and given that results also indicated that normal weight women are more likely to have higher ranking occupations, when accounting for education, this should be taken into account for future research. If normal weight women are likely to have higher ranking occupations and are more likely to spend more time on housework, is this potentially because they are living in larger houses because they have higher incomes? Size of house was not an option among the list of ATUS variables, but average household size could be computed by region and thus inputted in the regression analysis.

Table 3.1 Weighted Descriptive Statistics for ATUS Sample

Variable	Definition	Mean/Proportion (n = 13,323)
NORMAL WEIGHT	BMI between 18.5 and 24.9	0.42
OVERWEIGHT	BMI between 25 and 29.9	0.30
OBESE	BMI greater or equal to 30	0.28
BMI	weight (kg) / [height (m)]^2	27.45
AGE	1 = less than or equal to 45 0 = greater than 45	0.53
SCHOOLING	1 = more than high school level education 0 = high school degree or less	0.61
MARRIED	1 = married 0 = never married, widowed, or divorced	0.64
CHILDREN	Average number of children in the household	0.91
YOUNG CHILDREN	Children between the ages of 1 and 2	0.07
HEALTH	1 = excellent, very good, and good health 0 = fair and poor health	0.85
EMPLOYED	1 = in labor force 0 = not in labor force	0.75
DAY OF WEEK	1 = weekday 0 = weekend	0.71
POVERTY	1 = household income greater than 185% of poverty threshold 0 = household income less than or equal to 185% of poverty threshold	0.72
HOUSE TYPE	1 = house, apartment, or flat 0 = other types of housing	0.95
HOLIDAY	1 = interview day was a holiday 0 = interview day wasn't a holiday	0.02
RACE	1 = White 0 = non-White	0.81
TENURE	1 = owned or rented for cash 0 = occupied without payment	0.99
KID1TO2	1 = children between the ages of 1 and 2 living in household present 0 = no children between the ages of 1 and 2 living in household present	0.07
REGION	1 = South 0 = Northeast, Midwest, or West	0.36
FOOD STAMP	1 = does not receive food stamps 0 = receives food stamps	0.92
YEAR	1 = survey year is 2006 0 = survey year is 2007 or 2008	0.33

Table 3.2 Regression for Time Spent in Housework, BMI as Continuous Measure

Variable	**Parameter Estimate**	**Standard Error**	***t* Value**	**Pr > |t|**
Intercept	368.61**	46.53	7.92	<.0001
BMI	-6.66**	1.61	-4.13	<.0001
AGE_CAT	-0.20	3.31	-0.06	0.9513
DAY_CAT	-25.17**	3.11	-8.08	<.0001
EMPSTAT_CAT	-91.67**	3.54	-25.89	<.0001
EDUC_CAT_D	-7.43	3.14	-2.36	0.018
MARST_CAT_D	40.17**	3.29	12.2	<.0001
GENHEALTH_CAT	19.53**	4.34	4.5	<.0001
HH_NUMKIDS	39.66**	1.46	27.09	<.0001
HOLIDAY	23.90**	10.85	2.2	0.0276
WHITE_NH	18.11**	3.27	5.53	<.0001
KID1TO2	75.53**	5.82	12.98	<.0001
TENURE_CAT	7.37*	3.76	1.96	0.05
POVERTY	-12.47**	3.78	-3.3	0.001
R-square	**0.190**		***F*-value**	**237.19**
Adjusted R-square	**0.190**			

***p*<0.10, ***p*<0.05**

Table 3.3 Regression for Time Spent in Housework Plus Travel, BMI as Continuous Measure

Variable	**Parameter Estimate**	**Standard Error**	***t* Value**	**Pr > |t|**
Intercept	327.55**	47.51	6.89	<.0001
BMI	-5.06**	1.64	-3.08	0.0021
AGE_CAT	-7.89**	3.45	-2.29	0.0223
DAY_CAT	-27.84**	3.28	-8.49	<.0001
EMPSTAT_CAT	-84.14**	3.84	-21.94	<.0001
EDUC_CAT_D	-6.74**	3.31	-2.04	0.0417
MARST_CAT_D	38.15**	3.44	11.08	<.0001
GENHEALTH_CAT	16.42**	4.60	3.57	0.0004
HH_NUMKIDS	60.43**	2.20	27.5	<.0001
HOLIDAY	25.71**	11.19	2.3	0.0216
WHITE_NH	15.43**	3.46	4.46	<.0001
TENURE_CAT	6.21	3.98	1.56	0.1189
POVERTY	-10.56**	4.04	-2.62	0.0089
KID1TO2	75.26**	7.00	10.74	<.0001
R-square	**0.174**	***F*-value**	**185.73**	
Adjusted R-square	**0.173**			

***p*<0.10, ***p*<0.05**

Table 3.4 Regression for Time Spent in Housework and BMI Strata

Variable	Parameter Estimate	Standard Error	*t* Value	Pr > |t|
Intercept	97.29**	6.10	15.95	<.0001
OVERWEIGHT	-6.17*	3.31	-1.86	0.0627
OBESE	-14.52**	3.46	-4.2	<.0001
AGE_CAT	-1.30	3.23	-0.4	0.6868
DAY_CAT	-24.68**	3.02	-8.16	<.0001
EMPSTAT_CAT	-90.04**	3.36	26.72	<.0001
EDUC_CAT_D	-8.84**	2.96	-2.99	0.0028
MARST_CAT_D	40.97**	3.12	13.11	<.0001
GENHEALTH_CAT	15.72**	4.19	3.75	0.0002
HH_NUMKIDS	39.67**	1.38	28.68	<.0001
HOLIDAY	26.96**	10.55	2.56	0.0106
RACE_CAT	15.97**	3.15	5.06	<.0001
TENURE_CAT	74.87**	5.66	13.23	<.0001
KID1TO2	6.57*	3.56	1.84	0.0654
R-square	0.196	***F*-value**	**250.16**	
Adjusted R-square	0.195			

******p***<0.10, *****p***<0.05**

Table 3.5 Regression for Time Spent in Housework Plus Travel and BMI Strata

Variable	Parameter Estimate	Standard Error	*t* Value	Pr > |t|
Intercept	96.80**	6.25	15.48	<.0001
OVERWEIGHT	-6.37*	3.40	-1.88	0.0607
OBESE	-15.23**	3.54	-4.29	<.0001
AGE_CAT	0.395	3.31	0.12	0.9049
DAY_CAT	-19.68**	3.10	-6.35	<.0001
EMPSTAT_CAT	-91.28**	3.45	26.43	<.0001
EDUC_CAT_D	-7.45**	3.03	-2.45	0.0141
MARST_CAT_D	42.82**	3.20	13.37	<.0001
GENHEALTH_CAT	16.28**	4.30	3.79	0.0002
HH_NUMKIDS	44.96**	1.41	31.71	<.0001
HOLIDAY	21.11*	10.81	1.95	0.051
RACE_CAT	15.51**	3.23	4.8	<.0001
TENURE_CAT	74.64**	5.80	12.87	<.0001
KID1TO2	5.70	3.65	1.56	0.1189
R-square	0.209	***F* Value**	271.33	
Adjusted R-square	0.208			

******p***<0.10, *****p***<0.05**

Table 3.6 Occupational Categories by Nam-Powers-Boyd (NPB) 2000 Scale and Number of Women in Each Occupation from ATUS Sample

Category	Scale	Number of Employed Women
1	90-100	692
2	80-89	2129
3	70-79	1108
4	60-69	892
5	50-59	865
6	40-49	1131
7	30-39	1015
8	20-29	868
9	10-19	441
10	1-9	425

Table 3.7 Occupation Category by Education Level

Category	**High School Degree or Less n/percentage**	**More than High School Degree n/percentage**
TOP OCCUPATIONS	854 (15%)	4832 (85%)
BOTTOM OCCUPATIONS	1971 (51%)	1909 (49%)

Table 3.8 Occupation and BMI Category

	TOP OCCUPATIONS *n*/percentage	**BOTTOM OCCUPATIONS *n*/percentage**
Normal Weight	2758 (48%)	1494 (39%)
Overweight	1608 (29%)	1209 (31%)
Obese	1320 (23%)	1177 (30%)

Table 3.9 Occupation Categories by BMI Category (high school degree or less)

	Normal Weight	**Overweight**	**Obese**
TOP OCCUPATIONS	37%	32%	31%
BOTTOM OCCUPATIONS	34%	33%	33%
Chi-square	**2.98**	***P*-value**	**0.2251**

Table 3.10 Occupation Categories by BMI Category (more than high school degree)

	Normal Weight	**Overweight**	**Obese**
TOP OCCUPATIONS	51%	28%	22%
BOTTOM OCCUPATIONS	43%	29%	28%
Chi-square	**33.95**	***P*-value**	**<0.0001**

Table 3.11. Top Occupations by BMI and Race/Ethnicity (more than high school degree)

	Non-Hispanic White	**Non-Hispanic Black**	**Non-Hispanic Asian**	**Hispanic**
NORMAL WEIGHT	53%	25%	74%	51%
OVERWEIGHT	27%	35%	21%	25%
OBESE	20%	39%	5%	23%
Chi-square	**220.9**		***P*-value**	**<.0001**

Table 3.12. Bottom Occupations by BMI and Race/Ethnicity (high school degree or less)

	Non-Hispanic White	**Non-Hispanic Black**	**Non-Hispanic Asian**	**Hispanic**
NORMAL WEIGHT	39%	21%	75%	28%
OVERWEIGHT	32%	34%	20%	36%
OBESE	29%	45%	5%	35%
Chi-square	**84.5**		***P*-value**	**<.0001**

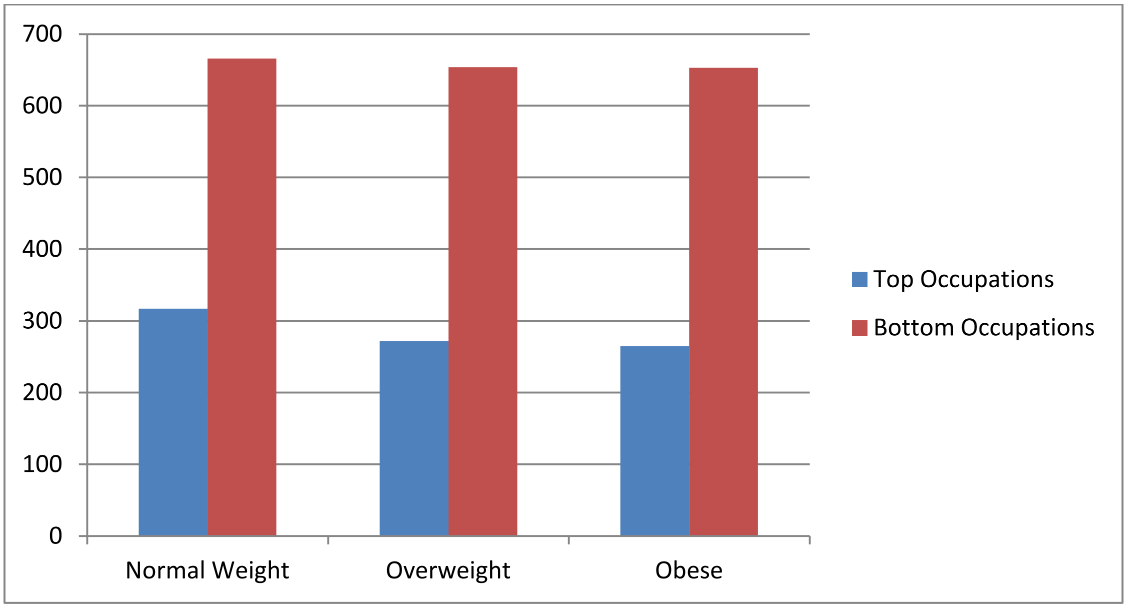

Figure 3.1 BMI, occupational status; high school degree or less

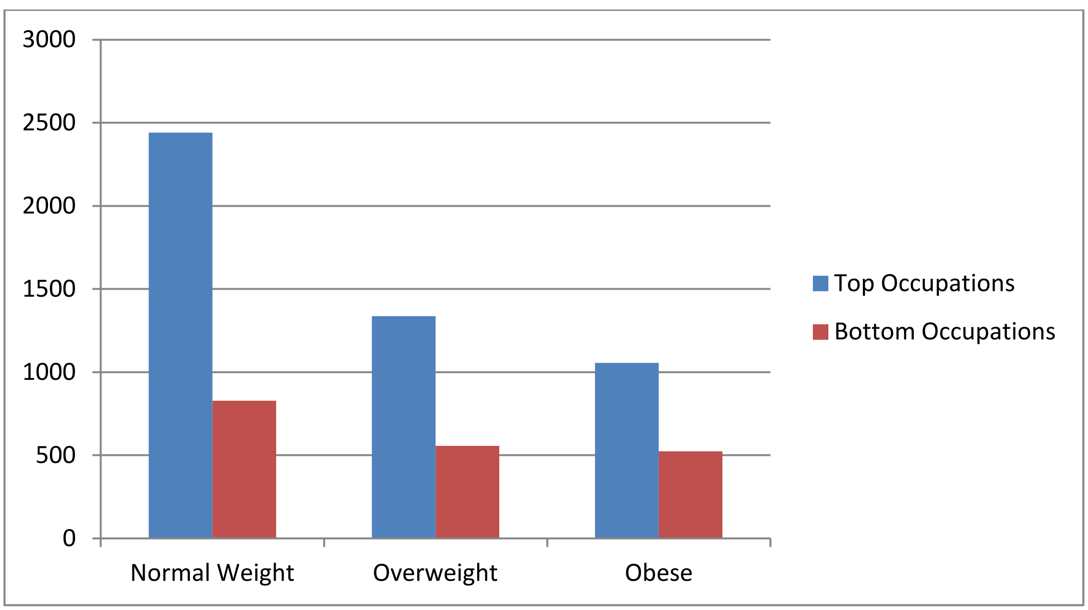

Figure 3.2 BMI, occupational status; more than a high school degree

CHAPTER 4

THE EFFECTS OF RACE AND ETHNICITY ON NONMARKET INDIRECT COSTS OF BEING OVERWEIGHT AND OBESE AMONG WOMEN

4.1 Introduction

Being overweight and obese imposes significant societal and economic burdens. Direct and indirect (as classically defined by the literature) costs of being overweight/obese are not only quite substantial, but they also vary greatly by race and gender. As discussed in Chapter 3, when analyzing the nonmarket costs of being overweight/obese, additional costs are imposed because being overweight/obese leads to decreases in time spent in household production. Also, as seen in Chapter 3, race is statistically significant in the regression analyses pertaining to differences in time spent in household production by BMI strata. Few studies have focused on the relationship between racial/ethnic factors and obesity-related time allocation. The goal of this chapter is to further analyze these indirect, nonmarket costs of obesity, specifically focusing on whether the penalty varies by racial/ethnic groups. Given that Chapter 3 found that being overweight and obese leads to decreased time spent in housework production, is there variation in this relationship across ethnic/racial groups? More specifically, knowing that obesity risk is related to race/ethnicity and given that housework time varies by race/ethnicity, are the observed differences from obesity or from racial/ethnic factors?

Differences in obesity rates among racial and ethnic groups stem from differences in behavior, attitudes, cultural norms, and access to healthy foods and safe locations to conduct physical activity (CDC, 2014), among other factors. Socioeconomic status (SES), which incorporates income, education, and occupation, is an influencing factor contributing to the large discrepancies in the obesity epidemic; prejudice, discrimination, and social stratification also contribute to the discrepancies (Kumanyika, 2008). As stated by Adler and Newman (2002), one of the most fundamental causes of health disparities is socioeconomic disparity. Health disparities arise if there are differences that occur based on differences in gender, race or ethnicity, education, income, disability, geographic location or sexual orientation (Adler & Rehkopf, 2008).

Studies show that living in poorer socioeconomic areas is associated with increased morbidity, mortality, and health-risk behavior (Virtanen et al., 2007). Even though obesity rates are rising across all social classes, both the prevalence of obesity and the severity of the consequences from obesity-related diseases are greater in certain places and among particular populations (Woodward-Lopez & Flores, 2006). Health disparities affect these populations to a greater extent due lack of resources or increased exposure to risk (Flaskerud et al., 2002).

Cultural norms and values contribute to the high variation in body weight because culture shapes eating patterns and activity levels (Sobal, 2001). Furthermore, increased immigration and thus changing and developing cultures have had significant effects in terms of increases in obesity levels. Cultural differences may also increase the risk of obesity during gestation, infancy, childhood, and adolescence through higher rates of female obesity during pregnancy and maternal diabetes during pregnancy (Kumanyika, 2008). Higher levels of food consumption during pregnancy, unhealthy childhood feeding habits, and inadequate levels of physical activity are frequently shaped by parental attitudes and practices.

The physical environment, which in large part is shaped by one's socioeconomic status, is a large barrier to physical activity as it increases the reliance on TV and a more sedentary lifestyle. The physical environment not only matters in terms of physical activity, but also in terms of limited access to supermarkets, which contributes to higher obesity levels. Access to supermarkets is an important factor in obtaining healthy food for reasonable prices, especially among those of lower socioeconomic status.

4.2 Obesity and Overweight Levels by Racial/Ethnic Groups

Recent national estimates revealed that among adults (age-adjusted), 71.3% of adult men are overweight/obese, whereas for adult women the rate is 65.8%. Of adult women, 35.5% are obese and 32.2% of adult men are obese (Ogden et al., 2014). Within wealthier nations, both minority and rural populations have the highest rates of obesity (Swinburn et al., 2004). Recent trends show that between 2009 and 2012 there was a greater percentage of U.S. adult women who were of normal weight in comparison to adult men (32.6% and 26.1%, respectively). For those overweight, the percentage was higher for men than women (37.9% and 28.3%, respectively) and in the obese category, women had a higher percentage than men (36.4% and 35.1%, respectively).[15]

Race, ethnicity, and cultural aspects of obesity/overweight are important factors to take into account as obesity and overweight rates vary greatly by race/ethnic groups;

[15] Data come from statistics provided by the Centers for Disease Control and Prevention (2013).

among adults in the United States, non-Hispanic Blacks have the highest prevalence of obesity (age-adjusted), followed by Hispanics and then non-Hispanic Whites (CDC, 2014). Data show that significant racial/ethnic differences exist in the rates of obesity, especially for women (Wang & Beydoun, 2007).

When the data are disaggregated, they expose considerable variation by race/ethnicity and gender. For adult men, statistics indicate that 31.9% of non-Hispanic White men were obese, whereas 37.3% of non-Hispanic Black men were obese; in comparison, 33% of non-Hispanic White women were obese and 49.6% of non-Hispanic Black women were obese (Ogden et al., 2014). Trends show that, between 2009 and 2012, among non-Hispanic Black women, 16% were normal weight, 24.2% were overweight, and 58% were obese; among Hispanic women, 20.1% were normal weight, 31.7% were overweight, and 47.6% were obese; among non-Hispanic White women, 35.9% were normal weight, 28.2% were overweight, and 32.7% were obese (CDC, 2013).

Data provided by the Behavioral Risk Factor Surveillance Survey (BRFSS) indicate that the prevalence of obesity is much lower among Asian Americans than other groups, but there is significant variation between different Asian groups as the prevalence among Native Hawaiians/Pacific Islanders is much higher in comparison. Asian Americans had the lowest percentage rate of obesity (11.6%), whereas American Indians and Alaska Natives had obesity rates of 39.9% and Native Hawaiians/Pacific Islanders' rates were 43.5% (U.S. Department of Health and Human Services, 2012)

Among women, obesity prevalence increases as education decreases. For example, 23.4% of women with college degrees are obese, whereas 42.1% of those with less than a high school education are obese (Ogden et al., 2010). Women with higher incomes are less likely to be obese than those with lower incomes, and those with college degrees are less likely to be obese compared with less educated women. In fact, poorly educated women are two to three times more likely to be overweight than those with more schooling (Flegal et al., 2012). Research analyzing the relationship between obesity and income indicates that among women obesity prevalence increases as income decreases, specifically among non-Hispanic White women (Ogden et al., 2010).

4.3 Obesity-Related Wage Penalties

Before analyzing race/ethnicity patterns in nonmarket effects of obesity, the question as to whether there are race/ethnic effects in market impacts, stemming from obesity, arises. Research indicates that there are significant obesity-related wage penalties; just like gender or race, obesity is a discriminatory factor in regards to hiring or promoting a candidate (Lempert, 2007). Research on labor market outcomes shows that appearance affects earnings (DeBeaumont, 2009; Hamermesh & Biddle, 1994; Persico et al., 2004), and, on average, obese females earn 2-8% less than their normal weight counterparts (Gregory & Ruhm, 2011). Obesity-related discrimination is most pronounced in females as studies have found a negative correlation between body weight and wages; such obesity-related wage penalties, for most studies, do not exist for males (Cawley, 2004).

There are several mechanisms through which obesity-related wage penalties can arise. Obesity-related wage penalties may arise due to the fact that obesity increases the risk of health problems, which in turn could diminish an individuals' capacity to work.

On the other hand, obesity-related wage penalties exist if employers discriminate against obese workers (Lindeboom, Lundborg, & van der Klauuw, 2010). Studies indicate that those who have above average looks have a wage advantage (Hamermesh & Biddle, 1994) while another study (DeBeaumont, 2009) indicated that only obese females who are in sales and service occupations receive a wage penalty.

Before 2004, Baum and Ford noted that there have only been four studies that utilize multivariate regression analysis to study the effects of obesity on wages in the United States. Also, another limitation is that the evidence is mixed as even when studies use the same dataset, there are differences in econometric techniques utilized. Hence, the economics literature is limited in how race/ethnicity contributes to obesity-related wage penalties as few studies have focused on this issue.

Utilizing the National Longitudinal Survey of Youth data (NLSY), Baum and Ford (2004) found a 6.1% wage penalty for obese women, compared to a 3.4% wage penalty for obese men; on the other hand, Register and Williams (1990) indicated the wage penalty for obese women is 12% but there are no significant effects for males; Loh (1993) indicated that there is no obesity-related wage penalty for men or women; Averett and Korenman (1996) found that obese women suffer a 10-24% wage penalty and men suffer an obesity wage penalty of about 8%, though overweight African American females are not penalized; and Pagan and Davila (1997) found that obesity reduces females wages, with variation across occupations, but not wages of males.

Another study, again utilizing NLSY data, compared outcomes when running ordinary least squares (OLS) versus accounting for endogeneity, such as utilizing instrumental variables (IV). Cawley (2004) showed that when utilizing OLS, BMI and weight had negative and statistically significant coefficients. The results indicated that heavier White females, Black females, Hispanic females, and Hispanic males tend to earn less, and heavier Black males tend to earn more. An increase of two standard deviations from the mean weight was associated with a 9% decreases in wages for non-Hispanic White women, a 4.7% decrease in wages for non-Hispanic Black women, and a 6.8% decreases in wages for Hispanic females (Cawley, 2004). On the other hand, when utilizing the IV approach to account for endogeneity, the results indicated that the hypothesis that weight does not lower wages can be rejected only for White females where an increase in two standard deviations from the mean weight in pounds is associated with an 18% decrease in wages.

Given that higher self-esteem has a positive relationship with wages (Mocan & Tekin, 2009; Waddell, 2006), obesity-related penalties could be present for non-Hispanic White women but not for non-Hispanic Black women due to the fact that there are cultural differences regarding the perception of obesity. Non-Hispanic Black women, in comparison to Hispanic and non-Hispanic White women, face fewer negative perceptions regarding weight (Lovejoy, 2001). As such, given that obesity-related wage penalties could be influenced, to some degree, by self-esteem and confidence, then perhaps non-Hispanic Black women are able to limit the negative effects associated with weight (DeBeaumont, 2009).

Which occupations the obesity-related wage penalty affects most is debatable; studies showed that professional women are more likely, in comparison to nonprofessional women, to report employment discrimination (e.g., Carr & Friedman, 2005) while another study showed no statistically significant connection between weight and pay for women in regard to professional, managerial, and technical occupations (e.g., DeBeaumont, 2009).

4.4 Time Spent in Housework by Race/Ethnicity

Both gender and racial/ethnic differences exist in regard to housework. However, studies pertaining to the matter have focused more on gender discrepancies than racial/ethnic ones. Data show that women, in all racial/ethnic groups, do more housework than men (Wight, Bianchi, & Hunt, 2013). According to the BLS (2013), women spend on average twice as much time on preparing food and drink, three times as much time doing interior cleaning, and four times as much time doing laundry in comparison to men.

Few studies have focused on how women of different racial/ethnic groups spend their time as the majority of the studies focus more on gender-role attitudes related to household-attitudes that arise. Studies concluded that non-Hispanic Black women spend less time on housework than non-Hispanic White women (Brines, 1994; Wight, Bianchi, & Hunt, 2013). When analyzing racial/ethnic groups, Hispanic women, in comparison to other women, spend the most time in housework (3.2 hours per day, on average). Non-Hispanic White and non-Hispanic Asian women spend close to 2.6 hours per day on housework, and non-Hispanic Black women spend, on average, 2.1 hours per day on housework (Wight, Bianchi, & Hunt, 2013). It should be noted, however, that this study (Wight, Bianchi, & Hunt, 2013) concentrated on gender-gap differences in housework and not on why there are differences in time spent in housework in different racial/ethnic groups. Questions arise as to why housework varies among women of different racial/ethnic groups; for example, does the variation stem from differences in household composition or number of children, on average, per household? Or do the differences in housework stem from socioeconomic differences or are they health/BMI related?

As seen from the literature, among the racial/ethnic groups studied, non-Hispanic Black women have been found to spend the least amount of time in housework, in comparison to non-Hispanic White and Hispanic women. Given that non-Hispanic Black women are more likely to be obese than their White counterparts, the possibility exists that the housework differences are a function of the housework obesity penalty rather than some racial/cultural difference in housework. This is the guiding thought in this chapter.

4.5 Methodology

As in Chapter 3, in order to measure the penalty for being obese or overweight, this chapter will use a time-use approach, utilizing the utility-maximization model and household production model framework, discussed in Chapter 3. From the utility-maximization model, it was inferred that weight is a function of housework (and hence housework is a function of weight). From the above discussion, it is clear that race/ethnicity influences weight through cultural norms and preferences and housework is also potentially influenced by cultural norms and cultural preferences as well. Hence, weight and amount of housework performed are both a function of race/ethnicity.

In Chapter 3 it was determined that for the overall population, obese and overweight women spend, in comparison to normal weight women, less time on housework. Whether this relationship holds, when disaggregating by racial/ethnic group, is the focus of this chapter. Once again, the prediction regarding how obesity/overweight changes time spent in housework was assumed to be ambiguous.

The data for the analysis come from the American Time-Use Survey, years 2006-2008 so as to utilize the Eating and Health (EH) Module data. For the EH Module, both height and weight are self-reported by the respondents. Total sample size for the EH Module for years 2006 to 2008 is 37,914 respondents. The ATUS sample is restricted to female respondents who are between the ages of 25 and 64 and whose BMI ranges from 18.5 to 64. The sample had these imposed age-restrictions so as to delete respondents who were more likely living with parents and older respondents, who were more likely to have complication health conditions that could impact BMI and housework time. The final sample size for this study is 13,323 women.

The ATUS categorizes respondents as “single” race and “two or more” races. This study categorized those who had two or more races as “other,” as long as they were not defined as Hispanic. The effects of overweight/obesity on household productivity were analyzed for the following racial/ethnic groups: non-Hispanic White, non-Hispanic Black, and Hispanic. If data permit (i.e., sufficient sample size), non-Hispanic American Indian/Alaskan Native, non-Hispanic Asian, and non-Hispanic Hawaiian Pacific Islander will be included in the analysis.

A limitation to this study is that although the ATUS is useful for obtaining obesity-related time use information, for the 3 years for which BMI data are available, there is an insufficient number of respondents from some at-risk cultural groups. The sample size for each racial/ethnic category is as follows: 8,966 non-Hispanic White (67%), 1,902 non-Hispanic Black (14%), 1,745 Hispanic (13%), 460 non-Hispanic Asian

(3%), 69 non-Hispanic American Indian/Alaskan Native (0.5%), and 30 non-Hispanic Pacific Islanders (0.2%). Given the small sample size for non-Hispanic American Indian/Alaskan Native and non-Hispanic Pacific Islanders, the women in these groups were labeled in the “other” category.

4.6 Regression Analysis

The goal is to ascertain the effect of differences in BMI strata on hours of housework by racial/ethnic group. The variables used (and description name) are identical to those used for Chapter 3. Once again the model is defined as:

Household activity (∑daily activities) = *function of* (BMI, education, number of children/number of members in the household, age, race, labor force status, general health status, marital status, type of household, poverty level, young children or not).

The dependent variable for the regression analysis is time spent in total housework where in one equation it includes travel (total_housework_lgp_travel), and in a separate analysis travel related to housework is not included (total_housework_lgp). The regression equations used are:

Model I:

$$\textbf{total\_housework\_lgp} = \beta_0 + \beta_1 BMI\_CAT\_OVERWEIGHT + \beta_2 BMI\_CAT\_OBESE + \beta_3 AGE\_CAT + \beta_4 DAY\_CAT + \beta_5 EMPSTAT\_CAT + \beta_6 EDUC\_CAT\_D + \beta_7 MARST\_CAT\_D + \beta_8 GENHEALTH\_CAT + \beta_9 HH\_NUMKIDS + \beta_{10} HOLIDAY + \beta_{11} HH\_TENURE + \beta_{12} POVERTY + \beta_{13} KID1TO2 + \mu$$

Model II:

$$\textbf{\textit{total\_housework\_lgp\_travel}} = \beta_{0} + \beta_{1}BMI\_CAT\_OVERWEIGHT + \beta_{2}BMI\_CAT\_OBESE + \beta_{3}AGE\_CAT + \beta_{4}DAY\_CAT + \beta_{5}EMPSTAT\_CAT + \beta_{6}EDUC\_CAT\_D + \beta_{7}MARST\_CAT\_D + \beta_{8}GENHEALTH\_CAT + \beta_{9}HH\_NUMKIDS + \beta_{10}HOLIDAY + \beta_{11}HH\_TENURE + \beta_{12}POVERTY + \beta_{13}KID1TO2 + \mu$$

The main hypothesis tested was whether the impact of BMI, and other covariates, on housework time varies by race/ethnicity. More specifically, the regression analysis focused on whether being a minority group member (i.e., non-Hispanic Black, non-Hispanic Asian, and Hispanic) and overweight or obese leads to more or less time spent in housework time in comparison to non-Hispanic overweight and obese White women, respectively. Thus the focus of this analysis is on a pooled regression, with ethnicity/race interaction variables. The null hypothesis was that the coefficient on each BMI-related interaction variable was equal to zero.

As the results center on how overweight and obese women compare to normal weight women, the samples were restricted to the following three datasets, given that non-Hispanic White women are the comparison group: non-Hispanic Black and non-Hispanic White women, non-Hispanic Asian and non-Hispanic White women, and Hispanic and non-Hispanic White women. This was done because it enables the regression analysis to have an appropriate comparison group.

4.6.1 Variables

The variables used for the regression analysis are those that were used in Chapter 3 with the exception that since the focus is on differences by race/ethnicity, interaction variables were created. The instruments used for the two-stage least squares modeling were region (location of respondent), foodstamp (whether the respondent is a participant in the food stamp program), and year of interview.

The independent variables used in the regression analysis were BMI category (using overweight and obese dummy categories to see the comparison to normal weight women); employment status; age (categorical variable); day of week (weekday or weekend); whether living quarters were owned, rented, or occupied without rent; marital status (married versus not-married categories); educational level (high school degree or less or more than high school degree); house type; number of kids in household; holiday (yes or no); general health status; if household income greater or less than 185% of poverty line; and whether own child was between the ages of 1 and 2.

To test for the differences between racial/ethnic groups, it was first established whether separate equations should be used for each race/ethnicity or whether interaction variables should be used; thus the Bartlett test was conducted. In order to pool across race/ethnic groups, the assumptions that are made are that each group is normally distributed, has the same variance, and each observation is independent. Given that the data are cross-sectional with only one observation per household, each observation is independent and given that the analysis utilized 2SLS estimation, it is assumed that housework is normally distributed. Thus the Bartlett test was conducted to analyze whether the variances of the two equations are the same; if variances are equal, the models should not be run separately and instead, interaction variables should be utilized. For each ethnic group (non-Hispanic Black, non-Hispanic Asian, and Hispanic), the *F*-values that were computed under the Bartlett tests (1.34, 0.82, and 0.995, respectively) were lower than the *F*-critical value of the test. Given this, the null hypothesis was not rejected and thus the models were run utilizing interaction variables.

Interaction variables were created so as to isolate the effects of race and ethnicity for differences in time spent on housework by BMI strata. Interaction variables were created for all independent variables and instrumental variables. The interaction variables for BMI strata were classified as follows: non-Hispanic White and overweight (overweight_white); non-Hispanic White and obese (obese_white); non-Hispanic Black and overweight (overweight_black); non-Hispanic Black and obese (obese_black); non-Hispanic Asian and overweight (overweight_asian); non-Hispanic Asian and obese (obese_asian); and Hispanic and overweight (overweight_hispanic); Hispanic and obese (obese_hispanic). Incorporating the interaction variables, the regression equation is given by form: [16]

Model I:

$$\textbf{\textit{total\_housework\_lgp}} = \beta_0 + \beta_1 BMI\_CAT\_OVERWEIGHT + \beta_2 BMI\_CAT\_OBESE + \beta_3 BLACK + \beta_4 OVERWEIGHT\_BLACK + \beta_5 OBESE\_BLACK + \beta_6 AGE\_CAT + \beta_7 AGE\_BLACK + \beta_8 DAY\_CAT + \beta_9 DAY\_BLACK + \beta_{10} TENURE\_CAT + \beta_{11} TENURE\_CAT\_BLACK + \beta_{12} EMPSTAT\_CAT + \beta_{13} EMPSTAT\_CAT\_BLACK + \beta_{14} EDUC\_CAT + \beta_{15} EDUC\_CAT\_BLACK + \beta_{16} MARST\_CAT + \beta_{17} MARST\_CAT\_BLACK + \beta_{18} HOUSETYPE\_CAT + \beta_{19} HH\_NUMKIDS\_BLACK + \beta_{20} HOLIDAY + \beta_{21} HOLIDAY\_BLACK + \beta_{22} GENHEALTH\_CAT + \beta_{23} GENHEALTH\_CAT\_BLACK + \beta_{24} POVERTY + \beta_{25} POVERTY\_BLACK + \beta_{26} KID1TO2 + \beta_{27} KID1TO2\_BLACK + \mu$$

[16] Given restraints provided by dummy variables regarding the interaction terms, the interaction models run were non-Hispanic Black, non-Hispanic Asian, and Hispanic women compared to non-Hispanic White.

Model II:

$$\textbf{\textit{total\_housework\_lgp\_travel}} = \beta_0 + \beta_1 BMI\_CAT\_OVERWEIGHT + \beta_2 BMI\_CAT\_OBESE + \beta_3 BLACK + \beta_4 OVERWEIGHT\_BLACK + \beta_5 OBESE\_BLACK + \beta_6 AGE\_CAT + \beta_7 AGE\_BLACK + \beta_8 DAY\_CAT + \beta_9 DAY\_BLACK + \beta_{10} TENURE\_CAT + \beta_{11} TENURE\_CAT\_BLACK + \beta_{12} EMPSTAT\_CAT + \beta_{13} EMPSTAT\_CAT\_BLACK + \beta_{14} EDUC\_CAT + \beta_{15} EDUC\_CAT\_BLACK + \beta_{16} MARST\_CAT + \beta_{17} MARST\_CAT\_BLACK + \beta_{18} HOUSETYPE\_CAT + \beta_{19} HH\_NUMKIDS\_BLACK + \beta_{20} HOLIDAY + \beta_{21} HOLIDAY\_BLACK + \beta_{22} GENHEALTH\_CAT + \beta_{23} GENHEALTH\_CAT\_BLACK + \beta_{24} POVERTY + \beta_{25} POVERTY\_BLACK + \beta_{26} KID1TO2 + \beta_{27} KID1TO2\_BLACK + \mu$$

4.7 Results

4.7.1 Descriptive Statistics

Weighted descriptive statistics are given in Table 4.1. In order to examine if statistically significant differences in time use and BMI exist between racial/ethnic groups, an analysis of variance (ANOVA) was performed. It establishes whether the means of the groups are equal through an F-test. These statistics are provided in Table 4.2. The racial/ethnic groups analyzed were non-Hispanic White, non-Hispanic Black, non-Hispanic Asian, and Hispanic women.

Differences between racial/ethnic groups were seen in education and marital status. Approximately 66% of non-Hispanic White and 77% of non-Hispanic Asian women have more than a high school degree, while approximately 53% of non-Hispanic Black women, and 38% of Hispanic women have more than a high school degree. Non-Hispanic Asian women are more likely to be married (80%), whereas 70% of non-Hispanic White women, 62% of Hispanic women, and only 35% of non-Hispanic Black women are married. ANOVAs showed statistically significant results for both education and marital status between the groups.

Analyzing food stamp recipients, close to 22% of non-Hispanic Black women and 15% of Hispanic women receive food stamps, whereas only 5% of non-Hispanic White women and 3% of non-Hispanic Asian women receive food stamps. From the sample, 77% of non-Hispanic White, 75% of non-Hispanic Black, 73% of non-Hispanic Asian, and 68% of Hispanic women are employed. For those who answered family's total annual income, roughly 48% had family incomes less than or equal to $49,999. Breaking this down by racial/ethnic group, the following observations are made: 27% of non-Hispanic Asian have a family income of less than $49,999, whereas 63% of Hispanic and 68% of non-Hispanic Black women have family incomes of less than $49,999 per year (ANOVAs indicated statistically significant results). Non-Hispanic White and non-Hispanic Asian women had the highest percentage of households whose income was greater than 185% of the poverty threshold (80% and 78%, respectively), while 50% of non-Hispanic Black, and 47% of Hispanic women had household incomes that were greater than 185% of the poverty threshold.

In this sample, 88% of non-Hispanic White women, 85% non-Hispanic Asian women, 79% of Hispanic women, and 76% of non-Hispanic Black women responded that they were in good health. Non-Hispanic White women had the highest percentage of employed women (77%), followed by non-Hispanic Black women (75%), non-Hispanic Asian women (73%), and Hispanic women (68%). Percent of women who were 45 years of younger by racial/ethnic group are as follows: 49% non-Hispanic White, 54% non-Hispanic Black, 67% non-Hispanic Asian, and 70% Hispanic were 45 years of younger. Hispanic women had, on average, the highest number of children (1.5), followed by non-Hispanic Black (1.03), non-Hispanic Asian (0.87), and non-Hispanic White (0.79). Non-

Hispanic Asian and Hispanic women were more likely to have children between the ages of 1 and 2 in the household (11% each) than non-Hispanic White or non-Hispanic Black (close to 6% each).

Discrepancies exist between racial/ethnic groups and BMI strata, where for all racial/ethnic normal weight was defined by a BMI that is between 18.5 and 25, overweight is defined as a BMI between 25 and 30, and obese is a BMI greater or equal to 30. Non-Hispanic Asian women have the highest percentage of women in the normal weight category (70%), followed by non-Hispanic White women (46%). On the other hand, only 34% of Hispanics are in the normal weight category, and 22% of non-Hispanic Black are normal weight.

Analyzing the composition of those in overweight category, the data show that non-Hispanic Black women have the highest percentage of overweight women; 35% of non-Hispanic Black women are overweight, 33% of Hispanic are overweight, 29% of non-Hispanic White women are overweight, and 24% of non-Hispanic Asian women are overweight. In the obese category, from the women in the sample, 43% of non-Hispanic Black women are obese, 34% of Hispanic women are obese, 25% of non-Hispanic White women are obese, and 6% of non-Hispanic Asian women are obese.

Analyzing total number of women who are overweight or obese for each racial/ethnic group, 77.6 % of non-Hispanic Black women, and 65.7% of Hispanic women, 53.8% of non-Hispanic White women, and 29.8% of non-Hispanic Asian women are overweight or obese. In comparison to national studies, 82.2% of non-Hispanic Black women, 79.3% of Hispanic women, 60.9% of non-Hispanic White women, and 34.4% of non-Hispanic Asian women are obese or overweight (CDC, 2014).

Table 4.2 shows the ANOVAs for BMI; results indicated that the *F*-value obtained was greater than the *F*-critical value at the 1% level, hence, we are able to reject the null hypothesis that there is no variation by cultural group membership. When analyzing differences by racial/ethnic groups, the outcome showed that mean BMI is lowest for non-Hispanic Asian women and highest for non-Hispanic Black women. Average BMI for the racial/ethnic groups was as follows: 26.8 for non-Hispanic White women, 30.3 for non-Hispanic Black women, 23.5 for non-Hispanic Asian women, and 28.3 for Hispanic women.

On average, total time spent in housework, per day, is approximately 189 minutes for non-Hispanic White women, 142 minutes for non-Hispanic Black women, 209 minutes for non-Hispanic Asian women, and 223 minutes for Hispanic women. Including housework-related travel time, total time spent in housework is 199 minutes for non-Hispanic White women, 152 minutes for non-Hispanic Black women, 219 minutes for non-Hispanic Asian women, and 237 minutes for Hispanic women. ANOVA results for differences in time spent in housework showed statistically significant differences also exist for the racial/ethnic groups in terms of time spent in housework.

4.7.2 Regression Results

Table 4.3 and Table 4.4 present the results of the multiple regression models for Model I and Model II described above, which analyzed the effects specific to non-Hispanic Black in comparison to non-Hispanic White women. When comparing results by BMI strata, the reference group was normal weight women.

Statistically significant results were not found in either model for either coefficient terms on the interaction variables (being overweight and Black; being obese and Black). In Model I, the interaction variables that were statistically significant for non-Hispanic Black women were age, day, tenure, employment status, education level, number of children, holiday, poverty, and if a child was between the ages of 1 and 2. In Model II, the interaction variables that were statistically significant for non-Hispanic Black women were employment status, education level, number of children, holiday, and if a child was between the ages of 1 and 2.

Running Model I and Model II but focusing on non-Hispanic Asian women compared to non-Hispanic White women (Table 4.5 and Table 4.6) showed statistically insignificant results for the interaction terms for the BMI strata variables. When comparing Hispanic women to non-Hispanic White women, the sample size for non-Hispanic White women is 8,966 and for Hispanic women it is 1745. However, utilizing this group of Hispanic women would include racial/ethnic categories such as Asian Hispanic, Black Hispanic, and so forth. Given that the interaction term would not be a direct comparison to non-Hispanic White women, the Hispanic women analyzed were White Hispanic (n = 1642). Results (Table 4.7 and Table 4.8) do not show statistical significance for being overweight and Hispanic or obese and Hispanic, for either model.

4.7.3 Regression Analysis Utilizing BMI as a Continuous Measure

As testing for BMI strata did not provide any statistically significant results, the regressions were run to analyze whether utilizing BMI as a continuous measure would shed some light. Hence the models run for these regressions were:[17]

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[17] Again, each model was run separately to compare non-Hispanic Black, non-Hispanic Asian, and Hispanic to non-Hispanic White.

Model I:

$$\textbf{\textit{total\_housework\_lgp}} = \beta_0 + \beta_1 BMI + \beta_2 BLACK + \beta_3 BMI\_BLACK + \beta_4 AGE\_CAT + \beta_5 AGE\_BLACK + \beta_6 DAY\_CAT + \beta_7 DAY\_BLACK + \beta_8 TENURE\_CAT + \beta_9 TENURE\_CAT\_BLACK + \beta_{10} EMPSTAT\_CAT + \beta_{11} EMPSTAT\_CAT\_BLACK + \beta_{12} EDUC\_CAT + \beta_{13} EDUC\_CAT\_BLACK + \beta_{14} MARST\_CAT + \beta_{15} MARST\_CAT\_BLACK + \beta_{16} HH\_NUMKIDS + \beta_{17} HH\_NUMKIDS\_BLACK + \beta_{18} HOLIDAY + \beta_{19} HOLIDAY\_BLACK + \beta_{20} GENHEALTH\_CAT + \beta_{21} GENHEALTH\_CAT\_BLACK + \beta_{22} POVERTY + \beta_{23} POVERTY\_BLACK + \beta_{24} KID1TO2 + \beta_{25} KID1TO2\_BLACK + \mu$$

Model II:

$$\textbf{\textit{total\_housework\_lgp\_travel}} = \beta_0 + \beta_1 BMI + \beta_2 BLACK + \beta_3 BMI\_BLACK + \beta_4 AGE\_CAT + \beta_5 AGE\_BLACK + \beta_6 DAY\_CAT + \beta_7 DAY\_BLACK + \beta_8 TENURE\_CAT + \beta_9 TENURE\_CAT\_BLACK + \beta_{10} EMPSTAT\_CAT + \beta_{11} EMPSTAT\_CAT\_BLACK + \beta_{12} EDUC\_CAT + \beta_{13} EDUC\_CAT\_BLACK + \beta_{14} MARST\_CAT + \beta_{15} MARST\_CAT\_BLACK + \beta_{16} HH\_NUMKIDS + \beta_{17} HH\_NUMKIDS\_BLACK + \beta_{18} HOLIDAY + \beta_{19} HOLIDAY\_BLACK + \beta_{20} GENHEALTH\_CAT + \beta_{21} GENHEALTH\_CAT\_BLACK + \beta_{22} POVERTY + \beta_{23} POVERTY\_BLACK + \beta_{24} KID1TO2 + \beta_{25} KID1TO2\_BLACK + \mu$$

For non-Hispanic Black women statistically significant results were found for the interaction between race and BMI (for both Model I and Model II); statistically insignificant results were found for the race/ethnicity interaction terms for non-Hispanic Asian and Hispanic women (for both Model I and Model II). Using BMI as a continuous variable, the regression results show that a one-point increase in BMI leads to a 1.19 minute reduction in time spent in housework for non-Hispanic White women while a one-point increase in BMI leads to a 2.45-minute reduction in time spent in housework for non-Hispanic Black women (1.82 and 3.06, respectively, when including travel time). Results for BMI as a continuous measure are provided in Appendix B and C. From this output, the assessment can be made that there are additional penalties for increased BMI for non-Hispanic Black women, in comparison to non-Hispanic White women.

4.8 Discussion

When running the analysis testing for differences in race/ethnicity, no statistically significant results were found for the coefficients on the BMI strata interaction variables for non-Hispanic Black, non-Hispanic Asian, or Hispanic women. The goal of the interaction variable was to observe whether obesity matters more or less for the minority group members than the dominant non-Hispanic White members. The regression results show that there is not a lot of evidence that obesity has a greater or lesser impact for minority group members given that, only when using BMI as a continuous measure the analysis showed statistically significant results for non-Hispanic Black women.

The regression results show, however, that being obesity matters for non-Hispanic Black women, non-Hispanic Asian women, and Hispanic women the exact same way it matters for non-Hispanic White women. Given that we know that, in comparison to non-Hispanic White women, more non-Hispanic Black women are obese and spend, on average, less time on housework, this analysis helps explain part of the difference in housework time, and translates into less time spent in housework.

Limitations to this study are that this study relies on survey data; hence this study utilized self-reported measures of BMI. Also, the diary day stemmed from 1 observed day and thus may not be an accurate reflection as to how the individual spends their day usually. Also, time use is only an imprecise measure of productivity; there is no measure of output from these studies, hence productivity cannot be precisely measured. Data limitations also existed when analyzing the number of minority group women; clearly non-Hispanic White women composed the majority of the sample size. Hence further studies, and data collection, regarding time-use and minority group women are needed.

Two other limitations occurring from the dataset are that there is the absence of two variables that would be beneficial to incorporate in this study: size of house and cleanliness level of house. Both are important factors that contribute to time spent in housework. Also of note is that when utilizing cross-sectional data as such, one cannot argue causation.

After conducting the literature review for this chapter, it is known that non-Hispanic Black women spend, on average, less time on housework than non-Hispanic Asian, non-Hispanic White, and Hispanic women. However, the studies do not focus on why housework varies by race/ethnicity. This study can be used to further extend the literature by focusing on which factors influence housework time by race/ethnicity and why differences arise. For example, from the regression output it can be noted that having young children between the ages of 1 and 2 is statistically significant for all women; however, when analyzing the interaction variable, the results show that being non-Hispanic Black and having young children is statistically significant, in comparison to non-Hispanic White. The regression analysis shows that for all women, having young children increases time spent in housework; however, when analyzing the results interaction variable for young children, the results show that being non-Hispanic Black and having young children reduces time spent in housework by approximately 40 minutes per day, on average. This is not observed in any other racial/ethnic group. Thus, this study lends itself to further enhancing the literature as to why discrepancies exist in time in spent housework by racial/ethnic groups.

Table 4.1. Weighted Descriptive Statistics, ATUS Sample, by Racial/Ethnic Group

MEAN/PROPORTION (STANDARD DEVIATION)	Non-Hispanic White (*n* = 8966)	Non-Hispanic Black (*n* = 1902)	Non-Hispanic Asian (*n* = 460)	Hispanic (*n* = 1745)
NORMAL WEIGHT	0.46	0.22	0.70	0.34
OVERWEIGHT	0.29	0.35	0.24	0.31
OBESE	0.25	0.43	0.06	0.34
MORE THAN HIGH SCHOOL	0.66	0.53	0.77	0.38
MARRIED	0.70	0.35	0.80	0.62
45 YEARS OR YOUNGER	0.49	0.54	0.67	0.70
NUMBER OF CHILDREN	0.79 (0.013)	1.03 (0.04)	0.87 (0.06)	1.5 (0.05)
TOTAL HOUSEWORK	189.2 (2.40)	142.2 (4.82)	208.8 (11.5)	222.7 (5.76)
TOTAL HOUSEWORK (TRAVEL)	198.7 (2.46)	152.4 (5.04)	219 (11.8)	237.4 (6.01)
RECEIVES FOODSTAMPS	0.05	0.22	0.03	0.15
EMPLOYED	0.77	0.75	0.73	0.68
IN GOOD HEALTH	0.88	0.76	0.85	0.79
HOUSEHOLD INCOME GREATER THAN 185% OF POVERTY THRESHOLD	0.80	0.50	0.78	0.47
FAMILY INCOME LESS THAN $49,999	0.37	0.68	0.27	0.63
CHILD BETWEEN THE AGES OF 1 AND 2	0.06	0.06	0.11	0.11

Table 4.2 ANOVA Results

VARIABLE	***F*-VALUES**
BMI	178
NORMAL WEIGHT	158.08
OVERWEIGHT	7.13
OBESE	123.30
MORE THAN HIGH SCHOOL DEGREE	171.67
MARRIED	219.18
AGE CATEGORY	34.99
NUMBER OF CHILDREN	47.97
TOTAL HOUSEWORK	74.10
TOTAL HOUSEWORK (TRAVEL)	75.27
RECEIVES FOODSTAMPS	117.77
EMPLOYED	20.72
IN GOOD HEALTH	88.41
POVERTY	293.44
FAMILY INCOME	10.65
CHILD BETWEEN 1 AND 2 YEARS OLD	13.57
CRITICAL F VALUE (1% LEVEL)	**3.319**

Table 4.3 Two-Stage Least Squares Weighted Parameter Estimates of the Total Housework Equation for Non-Hispanic Whites and Non-Hispanic Black

Variable	**Parameter Estimate**	**Standard Error**	***t* Value**	**Pr > |t|**
Intercept	234.17**	9.67	24.23	<.0001
BLACK_NH	-53.14**	21.93	-2.42	0.0154
BMI_CAT_OVERWEIGHT	-4.47	3.91	-1.14	0.253
OVERWEIGHT_BLACK	-5.01	11.16	-0.45	0.6534
BMI_CAT_OBESE	-11.87**	4.18	-2.84	0.0045
OBESE_BLACK	-9.05	10.95	-0.83	0.4084
AGE_CAT	-7.73**	3.88	-1.99	0.0465
AGE_BLACK	16.25*	9.59	1.69	0.0903
DAY_CAT	-31.03**	3.62	-8.58	<.0001
DAY_BLACK	9.60	9.15	1.05	0.2942
HHTENURE	-14.87**	4.39	-3.39	0.0007
TENURE_BLACK	7.29	9.11	0.8	0.4235
EMPSTAT_CAT	-90.67**	4.18	-21.72	<.0001
EMPSTAT_CAT_BLACK	21.17**	10.80	1.96	0.05
EDUC_CAT_D	-13.59**	3.68	-3.7	0.0002
EDUC_CAT_D_BLACK	22.14**	8.97	2.47	0.0136
MARST_CAT_D	28.65**	3.90	7.35	<.0001
MARST_CAT_D_BLACK	8.64	9.37	0.92	0.3564
HH_NUMKIDS	47.63**	1.82	26.1	<.0001
KIDS_BLACK	-15.02**	4.00	-3.75	0.0002
HOLIDAY	37.57**	12.38	3.03	0.0024
HOLIDAY_BLACK	-59.14*	30.31	-1.95	0.0511
GENHEALTH_CAT	22.73**	5.59	4.06	<.0001
GENHEALTH_BLACK	-14.63	11.31	-1.29	0.196
POVERTY	-2.30	4.57	-0.5	0.6151
POVERTY_BLACK	-19.50*	10.07	-1.94	0.0529
KID1TO2	76.76**	7.03	10.93	<.0001
YOUNGKID_BLACK	-39.71**	18.54	-2.14	0.0322
R-Square	0.206		*F* Value	103.03
Adjusted R-Square	0.204			

***p*<0.10, ***p*<0.05**

Table 4.4 Two-Stage Least Squares Weighted Parameter Estimates of the Total Housework Equation Plus Travel for Non-Hispanic Whites and Non-Hispanic Black

Variable	**Parameter Estimate**	**Standard Error**	***t* Value**	**Pr > |t|**
Intercept	234.95**	9.90	23.74	<.0001
BLACK_NH	-56.09**	22.46	-2.5	0.0125
BMI_CAT_OVERWEIGHT	-4.62	4.00	-1.15	0.2484
OVERWEIGHT_BLACK	-6.23	11.42	-0.54	0.5858
BMI_CAT_OBESE	-13.21**	4.28	-3.08	0.002
OBESE_BLACK	-7.94	11.22	-0.71	0.4791
AGE_CAT	-6.45	3.97	-1.62	0.1045
AGE_BLACK	16.01	9.82	1.63	0.1033
DAY_CAT	-27.57**	3.70	-7.45	<.0001
DAY_BLACK	12.08	9.37	1.29	0.1973
HHTENURE	-14.34**	4.49	-3.19	0.0014
TENURE_BLACK	5.43	9.33	0.58	0.5605
EMPSTAT_CAT	-92.27**	4.28	-21.58	<.0001
EMPSTAT_CAT_BLACK	25.25**	11.06	2.28	0.0225
EDUC_CAT_D	-12.27**	3.76	-3.26	0.0011
EDUC_CAT_D_BLACK	21.78**	9.19	2.37	0.0178
MARST_CAT_D	29.00**	3.99	7.27	<.0001
MARST_CAT_D_BLACK	11.17	9.59	1.16	0.2445
HH_NUMKIDS	53.20**	1.87	28.47	<.0001
KIDS_BLACK	-16.03**	4.10	-3.91	<.0001
HOLIDAY	31.72**	12.68	2.5	0.0124
HOLIDAY_BLACK	-53.70*	31.04	-1.73	0.0837
GENHEALTH_CAT	21.44**	5.73	3.74	0.0002
GENHEALTH_BLACK	-13.28	11.58	-1.15	0.2516
POVERTY	0.65	4.68	0.14	0.8897
POVERTY_BLACK	-19.56*	10.31	-1.9	0.0579
KID1TO2	77.06**	7.19	10.71	<.0001
YOUNGKID_BLACK	-29.72	18.98	-1.57	0.1174
R-Square	0.218		***F* Value**	110.67
Adjusted R-Square	0.216			

***p*<0.10, ***p*<0.05**

Table 4.5 Two-Stage Least Squares Weighted Parameter Estimates of the Total Housework Equation for Non-Hispanic Whites and Non-Hispanic Asian

Variable	**Parameter Estimate**	**Standard Error**	***t* Value**	**Pr > |t|**
Intercept	234.17**	9.93	23.59	<.0001
ASIAN_NH	-86.49*	44.55	-1.94	0.0522
BMI_CAT_OVERWEIGHT	-4.47	4.01	-1.11	0.2657
OVERWEIGHT_ASIAN	-4.22	17.81	-0.24	0.8127
BMI_CAT_OBESE	-11.87**	4.29	-2.76	0.0057
OBESE_ASIAN	35.16	30.65	1.15	0.2515
AGE_CAT	-7.73*	3.98	-1.94	0.0525
AGE_ASIAN	-19.23	17.34	-1.11	0.2674
DAY_CAT	-31.03**	3.71	-8.36	<.0001
DAY_ASIAN	-1.16	16.59	-0.07	0.944
HHTENURE	-14.87**	4.50	-3.3	0.001
TENURE_ASIAN	65.84**	18.19	3.62	0.0003
EMPSTAT_CAT	-90.67**	4.29	-21.15	<.0001
EMPSTAT_CAT_ASIAN	-12.06	16.90	-0.71	0.4757
EDUC_CAT_D	-13.59**	3.78	-3.6	0.0003
EDUC_CAT_D_ASIAN	11.83	18.46	0.64	0.5218
MARST_CAT_D	28.65**	4.00	7.16	<.0001
MARST_CAT_D_ASIAN	7.51	18.69	0.4	0.6878
HH_NUMKIDS	47.63**	1.87	25.42	<.0001
KIDS_ASIAN	-3.53	7.72	-0.46	0.6478
HOLIDAY	37.57**	12.71	2.95	0.0031
HOLIDAY_ASIAN	58.35	58.98	0.99	0.3225
GENHEALTH_CAT	22.73**	5.74	3.96	<.0001
GENHEALTH_ASIAN	-5.71	22.22	-0.26	0.7971
POVERTY	-2.30	4.70	-0.49	0.6244
POVERTY_ASIAN	34.57*	18.71	1.85	0.0647
KID1TO2	76.76**	7.21	10.64	<.0001
YOUNGKID_ASIAN	8.53	25.55	0.33	0.7384
R-Square	0.207		*F* Value	89.75
Adjusted R-Square	0.205			

***p*<0.10, ***p*<0.05**

Table 4.6 Two-Stage Least Squares Weighted Parameter Estimates of the Total Housework Equation Plus Travel for Non-Hispanic Whites and Non-Hispanic Asian

Variable	**Parameter Estimate**	**Standard Error**	***t* Value**	**Pr > |t|**
Intercept	234.95**	10.15	23.16	<.0001
ASIAN_NH	-87.95*	45.53	-1.93	0.0534
BMI_CAT_OVERWEIGHT	-4.62	4.10	-1.13	0.2601
OVERWEIGHT_ASIAN	-0.49	18.20	-0.03	0.9785
BMI_CAT_OBESE	-13.21**	4.39	-3.01	0.0026
OBESE_ASIAN	39.47	31.33	1.26	0.2078
AGE_CAT	-6.45	4.07	-1.58	0.1132
AGE_ASIAN	-18.35	17.72	-1.04	0.3006
DAY_CAT	-27.57**	3.79	-7.27	<.0001
DAY_ASIAN	2.94	16.95	0.17	0.8622
HHTENURE	-14.34**	4.60	-3.12	0.0018
TENURE_ASIAN	65.31**	18.60	3.51	0.0004
EMPSTAT_CAT	-92.27**	4.38	-21.05	<.0001
EMPSTAT_CAT_ASIAN	-14.13	17.28	-0.82	0.4134
EDUC_CAT_D	-12.27**	3.86	-3.18	0.0015
EDUC_CAT_D_ASIAN	8.64	18.87	0.46	0.647
MARST_CAT_D	29.00**	4.09	7.09	<.0001
MARST_CAT_D_ASIAN	6.59	19.10	0.35	0.7301
HH_NUMKIDS	53.20**	1.92	27.77	<.0001
KIDS_ASIAN	-3.74	7.89	-0.47	0.6353
HOLIDAY	31.72**	13.00	2.44	0.0147
HOLIDAY_ASIAN	45.67	60.29	0.76	0.4487
genhealth_cat	21.44**	5.87	3.65	0.0003
GENHEALTH_ASIAN	4.99	22.71	0.22	0.8262
POVERTY	0.65	4.80	0.14	0.8924
POVERTY_ASIAN	26.36	19.13	1.38	0.1682
KID1TO2	77.06**	7.37	10.45	<.0001
YOUNGKID_ASIAN	2.51	26.11	0.1	0.9235
R-Square	0.220		*F* Value	96.84
Adjusted R-Square	0.217			

***p*<0.10, ****p*<0.05**

Table 4.7 Two-Stage Least Squares Weighted Parameter Estimates of the Total Housework Equation for Non-Hispanic Whites and Hispanic

Variable	**Parameter Estimate**	**Standard Error**	***t* Value**	**Pr > |t|**
Intercept	234.17**	9.89	23.69	<.0001
HISPANIC_TOTAL	-39.79	24.43	-1.63	0.1034
BMI_CAT_OVERWEIGHT	-4.47	4.00	-1.12	0.2638
OVERWEIGHT_HISPANIC	10.92	11.14	0.98	0.3269
BMI_CAT_OBESE	-11.87**	4.28	-2.78	0.0055
OBESE_HISPANIC	12.93	11.06	1.17	0.2425
AGE_CAT	-7.73*	3.97	-1.95	0.0516
AGE_HISPANIC	6.00	11.03	0.54	0.5867
DAY_CAT	-31.03**	3.70	-8.39	<.0001
DAY_HISPANIC	42.69**	9.70	4.4	<.0001
HHTENURE	-14.87**	4.49	-3.31	0.0009
TENURE_HISPANIC	25.90**	10.04	2.58	0.0099
EMPSTAT_CAT	-90.67**	4.27	-21.23	<.0001
EMPSTAT_CAT_HISPANIC	-10.14	10.32	-0.98	0.3257
EDUC_CAT_D	-13.59**	3.76	-3.61	0.0003
EDUC_CAT_D_HISPANIC	18.45**	10.29	1.79	0.073
MARST_CAT_D	28.65**	3.98	7.19	<.0001
MARST_CAT_D_HISPANIC	44.61**	9.83	4.54	<.0001
HH_NUMKIDS	47.63**	1.87	25.52	<.0001
KIDS_HISPANIC	-28.38**	4.06	-6.98	<.0001
HOLIDAY	37.57**	12.66	2.97	0.003
HOLIDAY_HISPANIC	-49.86	40.01	-1.25	0.2127
GENHEALTH_CAT	22.73**	5.72	3.97	<.0001
GENHEALTH_HISPANIC	-9.93	12.17	-0.82	0.4144
POVERTY	-2.30	4.68	-0.49	0.623
POVERTY_HISPANIC	-44.20**	10.66	-4.15	<.0001
KID1TO2	76.76**	7.19	10.68	<.0001
YOUNGKID_HISPANIC	-1.05	15.57	-0.07	0.9465
R-Square	0.213		*F* Value	104.31
Adjusted R-Square	0.211			

***p<0.10, **p<0.05**

Table 4.8 Two-Stage Least Squares Weighted Parameter Estimates of the Total Housework Equation Plus Travel for Non-Hispanic Whites and Hispanic

Variable	**Parameter Estimate**	**Standard Error**	***t* Value**	**Pr > |t|**
Intercept	234.95**	10.12	23.22	<.0001
HISPANIC_TOTAL	-55.73**	25.01	-2.23	0.0259
BMI_CAT_OVERWEIGHT	-4.62	4.09	-1.13	0.2589
OVERWEIGHT_HISPANIC	12.75	11.41	1.12	0.2635
BMI_CAT_OBESE	-13.21**	4.38	-3.02	0.0026
OBESE_HISPANIC	17.47	11.32	1.54	0.1228
AGE_CAT	-6.45	4.06	-1.59	0.1123
AGE_HISPANIC	9.22	11.29	0.82	0.4141
DAY_CAT	-27.57**	3.79	-7.28	<.0001
DAY_HISPANIC	50.09**	9.93	5.04	<.0001
HHTENURE	-14.34**	4.59	-3.12	0.0018
TENURE_HISPANIC	30.45**	10.27	2.96	0.003
EMPSTAT_CAT	-92.27**	4.37	-21.11	<.0001
EMPSTAT_CAT_HISPANIC	-13.96	10.56	-1.32	0.1862
EDUC_CAT_D	-12.27**	3.85	-3.19	0.0014
EDUC_CAT_D_HISPANIC	18.57**	10.54	1.76	0.078
MARST_CAT_D	29.00**	4.08	7.11	<.0001
MARST_CAT_D_HISPANIC	48.95**	10.06	4.87	<.0001
HH_NUMKIDS	53.20**	1.91	27.84	<.0001
KIDS_HISPANIC	-28.40**	4.16	-6.83	<.0001
HOLIDAY	31.72**	12.96	2.45	0.0144
HOLIDAY_HISPANIC	-49.58	40.96	-1.21	0.2261
GENHEALTH_CAT	21.44**	5.85	3.66	0.0003
GENHEALTH_HISPANIC	-4.24	12.46	-0.34	0.7335
POVERTY	0.65	4.79	0.14	0.8921
POVERTY_HISPANIC	-48.30**	10.91	-4.43	<.0001
KID1TO2	77.06**	7.36	10.48	<.0001
YOUNGKID_HISPANIC	-9.68	15.94	-0.61	0.5435
R-Square	0.227		*F* Value	113.45
Adjusted R-Square	0.225			

***p*<0.10, ****p*<0.05**

CHAPTER 5

AN ECONOMIC ASSESSMENT OF AN INTERVENTION TO INCREASE PHYSICAL ACTIVITY AMONG MINORITY WOMEN: THE UWAG STUDY

5.1 Introduction

With the rising rates and, subsequently, costs, of physical inactivity and obesity in the United States, substantial cost savings could be realized if physical activity increased among those who are sedentary, as well as those who are considered insufficiently active.[18] The focus of this chapter is to conduct a cost-effectiveness analysis (CEA) of a health intervention designed to increase physical activity and dietary nutrition among certain minority female populations in Utah, where the obesity crisis has been particularly acute and recalcitrant.

This chapter provides an evaluation of an ongoing coaching intervention associated with the Utah Women and Girls (UWAG) study. The program was developed using a community-based participatory research approach and addresses health behaviors related to obesity in five diverse cultural groups. Health disparities arise in these communities because many women in underserved communities face heightened risk for

[18] The Health and Human Services criterion for meeting physical activity guidelines for adults, aged 18-64, is at least 150 minutes of moderate intensity aerobic physical activity or 75 minutes of vigorous aerobic physical activity per week.

chronic diseases and disproportionately have fewer resources to address or remediate such risk. For example, the obesity epidemic disproportionately affects women and cultural minorities; hence, this subgroup of the population is especially vulnerable.[19] Even though the burden of disease falls heavily on those of lower socioeconomic status, most studies on physical intervention programs have not focused on high-risk groups. The objective of this chapter is to gauge the economic benefits associated with this community-based coaching intervention.

5.2 Background

One goal of the Healthy People 2020 guidelines, a nationwide program set by the US Department of Health and Human Services, is to promote increased levels of physical activity. Another goal pertains to dietary intake; Healthy People 2020 seeks to increase dietary intake, in the form of healthier alternatives. These are the goals that the UWAG health intervention targeted. Increases in physical activity levels reduce the risks of chronic disease (e.g., certain types of cancers, type 2 diabetes, and coronary heart disease) and mortality rates (Roux et al., 2008). Certain interventions have been found to increase physical activity (Kahn et al., 2002), but the degree of success depends on the type of intervention as well as the targeted population. Elements that help render interventions successful are setting goals; self-monitoring progress; careful planning; increased social capital of communities and neighborhoods; well-trained staff members; effective communication; community participation and ownership; targeting the social

[19] “High-risk woman” is defined as an individual more prone to having higher rates of obesity, who has, therefore, higher costs associated with the disease (see Chapters 2 and 4 for a more detailed discussion).

environment; counseling and providing help with behavior modification; educating the community; utilizing positive messages (e.g., positive self-talk); and sufficient resources (Culter, 2004; Kahn et al., 2002).

The UWAG study is an individually adapted health intervention. Such programs are tailored to individual needs and goals whereas other types of health interventions include point-of-decision prompts, school-based programs, social support programs, mass-media campaigns, and pharmaceutical and surgical interventions (O'Grady & Capretta, 2012). Though, generally speaking, more costly than other programs (e.g., mass media campaigns or school-based programs), individually adapted programs have been shown to have favorable results in increasing levels of physical activity (Kahn et al., 2002). However, few of these health interventions have been analyzed as to whether, besides increasing physical activity levels, they are cost-effective programs.

Under cost-effectiveness analysis, a cost-effectiveness ratio is estimated. The ratio measures the costs of the health intervention in comparison to the outcomes or consequences, commonly measured by quality-adjusted life years (QALYs) gained. QALYs are a standardized measure that represent gains in health, both in terms of the number of years of life lived and also the quality of life during those years lived. Calculation of QALYs is based on quality of life scores (utilities) that are obtained from preference-based utility-generating health-related quality of life (HRQL) measures (Muennig et al., 2006; Vainiola et al., 2011). The utility scale is a continuous measure from zero (utility assigned to death) to 1 (utility assigned to being in full health; Nord, 1999).[20]

[20] Using CEA in the United States as an explicit guide to policy decisions has gained only limited traction in part due to the fact that it has not been formally adopted (Weinstein, 2008).

5.2.1 QALYs Associated with Obesity and Physical Activity

Studies have found increased quality-of-life from reduction in obesity levels (e.g., Jia & Lubetkin, 2005; Muennig, Lubetkin, Jia & Franks, 2006; White, O'Neil, Kolotkin & Byrne, 2004). Obesity reduces QALYs due to its associations with decreased energy levels and the reduced capacity to perform activities such as walking, working, and participating in physical activity; increased negative general health perception; increased worry; and chronic bodily pain. Physical activity has been found to be associated with increased quality of life independent of its effect on obesity given its associated gains in terms of both reductions in medical costs and increased quality-of-life years (Jia & Lubetkin, 2005).

Obesity and physical inactivity impact daily functioning and, therefore, quality of life. Health-related quality of life can be diminished without having an impact on morbidity or other metabolic and physiologic markers (Kuschner & Foster, 2000; Muennig et al., 2006). Other reductions in quality of life, stemming from obesity, include physical functioning, public distress, sexual functioning, self-esteem, and work-related quality of life (White et al., 2004). Also, adults who are obese are more likely to report being in fair or poor health, having diabetes, and having hypertension in comparison to normal-weight adults (Muennig et al., 2006).

Not surprisingly, HRQL scores decrease with an increasing level of obesity. Those with severe obesity have the lowest scores although those with moderate obesity and overweight also are shown to have significantly lower scores. Obesity-related quality of life impairments vary by race and gender along certain metrics. Obesity-related depression is higher among women than men; relative to their normal weight counterparts, being overweight and obese has a much smaller effect for men, both in regards to health-related quality of life and mortality. One study assessed that men lost a total of 270,000 QALYs and women lost a total of 1.8 million QALYs due to being overweight and obese (Jia & Lubetkin, 2010).

Non-Hispanic Black women have the highest amount of QALYs lost due to obesity (0.0676 per person) and in comparison to non-Hispanic White women had 50% higher QALYs lost (Jia & Lubetkin, 2010; Muennig et al., 2006; White et al., 2004). However, within each cultural group, it is notable to mention that variances are not as profound; overweight non-Hispanic Blacks and Hispanics have similar health-related quality of life scores as normal weight non-Hispanic Blacks and Hispanics (Muennig et al., 2006).

Muennig et al. (2006) utilized data from the Medical Expenditure Panel Survey (MEPS) and National Health Interview Survey (NHIS) to calculate the burden of disease and quality-adjusted life years lost from obesity. Quality-adjusted life years lost to morbidity were calculated by taking the difference in HRQL scores for normal weight people versus overweight/obese people and then multiplying it by population who is overweight/obese (in the age category). Results showed that normal weight women lived 2.9 QALYs more than overweight women and 7.2 QALYs more than obese women.

Jia and Lubetkin's (2010) study analyzed QALYs lost due to obesity, focusing on gender and racial differences in lost life years utilizing Behavioral Risk Factor Surveillance Survey (BRFSS) data. Questions pertaining to state of an individual's physical and mental health, as well as questions related to whether physical activity was impaired were utilized. The authors utilized hazard models applied to state-level mortality data and obesity prevalence to calculate age-specific death rates by obesity status. Results showed that obesity-related QALYs lost, calculated by summing QALYs lost due to morbidity and future QALYs lost in expected life years due to premature deaths, more than doubled between 1993 and 2008 in the US.[21]

The study found that obese adults had significantly lower HRQL scores; these results held even in the absence of a chronic disease associated with obesity. For non-Hispanic Whites, the QALYs lost due to obesity were almost the same between men and women; QALYs lost for Hispanics is comparable to those of non-Hispanic White. Obesity contributed 0.0204 QALYs lost per person in 1993 and 0.0464 QALYs lost per person in 2008. Non-Hispanic Black women had the most QALYs lost due to obesity. In 2008, QALYs lost due to morbidity for non-Hispanic White women was 0.026 and QALYs lost due to mortality was 0.019; for non-Hispanic Black women, QALYs lost due to morbidity was 0.035 and QALYs lost due to mortality was 0.032 (Jia & Lubetkin, 2010).

Physical inactivity also affects quality of life, but few studies have researched QALYs gained from physical activity level increases; Sun et al. (2014) and Roux et al. (2008) have focused on quantifying QALYs gained from a physical activity interventions. Roux et al. focused on assessing cost-effectiveness among different community-based physical activity interventions, specifically focusing on seven physical activity intervention programs, stratifying by age and gender.

Roux et al. (2008) developed a Markov model from a societal perspective to estimate lifetime costs, health gains, and cost-effectiveness of population interventions.

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[21] Obesity-related QALYs lost were calculated by the total of QALYs lost due to morbidity and future QALYs lost, in expected life years, stemming from premature deaths.

BRFSS data were used to analyze age- and gender-specific physical activity data.[22] The authors estimated the annual probability of mortality as well as the probability of developing each disease, taking the median relative risk of each disease by physical activity category into consideration. To obtain data on quality-adjusted life years added from a physical intervention program, the authors used data from the 2001 National Health Interview Survey as a function of age, gender, disease, and physical activity level where results are cumulative over a 40-year time-horizon. The average discounted quality-adjusted life expectancy was calculated to be 14.77 years. Incremental QALYs gained from the physical health intervention programs analyzed improved average QALYs by 0.7 to 5.3 weeks, meaning between 0.014 and 0.102 QALYs per year, per person (Roux et al., 2008).

Limitations to this study include that when analyzing disease-specific parameters in order to value the annual expenditures per person, the authors calculate total expenditures for men and women separately. However, these annual per-person medical costs for men and women do not seem to take into account that costs vary by BMI strata, gender, and race/ethnicity. Though the analysis calculates QALYs gained from different physical intervention programs, the study does not incorporate race or ethnicity.

Sun et al. (2014) focused on QALYs gained from a 2-year physical activity intervention among adults who had or were at risk of osteoarthritis (OA), where physical activity was measured by accelerometers. The authors studied QALYs gained from three activity groups: inactive individuals, insufficiently active individuals, and active individuals. The authors of the study measured QALYs by using a health-related utility at

[22] The cohort was assumed to be healthy meaning individuals not having any of the following conditions: coronary heart disease, ischemic stroke, type II diabetes, breast cancer, or colorectal cancer.

baseline and then analyzing this health-related utility scale after the 2-year follow up. Higher QALYs were associated for those who were engaged in more physical activity, and that moving from either insufficiently active or inactive to active increases one's health outcomes. QALYs were calculated through health-related utility scores, derived from the Short-Form Health Survey, at baseline and at the end of the study.

Over the 2 years, for the full cohort and analyzing age-adjusted difference, 0.162 QALYs were gained for those who went from inactive to active. Analyzing women and adjusting for age, Sun et al. found QALYs improved 0.203 in 2 years for those who went from inactive to active and 0.084 in 2 years for those who went from insufficiently active to active. Taking socioeconomic factors into account, these numbers changed to 0.199 and 0.091, respectively. When analyzing only by BMI category, the authors found that those who were obese and went from inactive to active gained 0.157 QALYs over 2 years (adjusting for age), whereas those who were insufficiently active gained 0.028 QALYs over 2 years (adjusting for age).

5.3 Methodology

Data for this study are from the Coalition for a Healthier Community for Utah Women and Girls (UWAG), which is a partnership with Community Faces of Utah (CFU), an organization representing five underserved communities, the University of Utah, and the Utah Department of Health. The project received funding from the Office of Women's Health (OWH) of the U.S. Department of Health and Human Services. The UWAG health intervention is a coalition of academic, public health, and community representatives and uses community-based participatory research (CBPR). The health intervention program is tailored to address not only health behavior concerns directly, but also indirectly, through cultural and gender norms. Cost-effectiveness analyzed will be conducted for three assessments: for the program as a whole and then separately by the low-intensity and high-intensity groups. Physical activity levels are compared at baseline and at 1 year for those who have completed the surveys.[23]

Community-based participatory research focuses on increasing health equity by increasing community engagement and social action. Community health care challenges are, among others, developing, implementing, and sustaining effective strategies to eliminate health disparities. Through CBPR, a voice is given to underserved communities in the health intervention, which increases the likelihood of a health intervention's success (Wallerstein & Duran, 2010). The five underserved communities in the UWAG health intervention program are African immigrants, African Americans, Hispanics/Latinas, American Indians/Alaskan Natives, and Pacific Islanders.

Most of the UWAG participants in the Hispanic/Latina group are from Mexico, with a few from Argentina and Guatemala; all Latinas in the program are immigrants. The participating women in the African immigrant category are primarily from Burundi and Rwanda. The tribes represented in the American Indian/Alaskan Native group are Navajo, Northern Ute, Lakota Sioux, Paiute, Eastern Shoshone, Sioux, Arapahoe, Shoshone Paiute, Goshute, Dine, Northern Arapaho, Pomo/Walylaki, and Tlingit. Pacific Islander immigrant women identify themselves as Samoan, Tongan, Fijian, Maori, Hawaiian, Rarotonga (Cook Islands), Tokelau, and White.

The women were recruited and randomized into two arms: receipt of either quarterly or monthly in-person wellness coaching for a 12-month period. Women

[23] Data for the UWAG intervention were downloaded February 10th, 2015.

assigned to monthly coaching also participated in monthly group activities focused on increasing knowledge of healthy behaviors and building social support. Coaching was conducted by lay wellness coaches who were members of their respective communities; coaches were recruited by community leaders and trained by University of Utah faculty and staff.

The study is focused on assessing the effectiveness of a coaching intervention designed to increase women's physical activity levels and improve their dietary habits through motivational interview-based wellness coaching and goal setting. One aim of the analysis, which is the focus of this chapter, is to gauge the economic benefits associated with the community-based coaching intervention, using cost-effectiveness analysis.

The project development for the UWAG health intervention was conducted in two phases. The first phase (Phase I) entailed a needs assessment for the community and the second phase (Phase II) entailed the randomized trial for the women. In Phase I (needs assessment), a thorough literature review and analysis of Utah's Behavioral Risk Factor Surveillance Survey (BRFSS) was conducted in order to explore cultural needs and gaps among minority group women. The UWAG health intervention program asks two main questions: whether a wellness coaching approach is more effective when implemented using an evidence-based, lifestyle, gender-focused intervention and if there are differences ascertained from the high and low intensity programs, and the cost-effectiveness of these two arms of the intervention. To the degree that wellness coaching is more effective than other types of health intervention programs, a question arises as to whether the incremental improvement in health outcomes warrants the additional costs.

The intervention sets the goals of behavioral changes with the healthy people

(HP) 2020 targets in mind, which include: NWS–14: increase the contribution of fruits to the diets of the population aged 2 years and older; NWS–15: increase the variety and contribution of vegetables to the diets of the population aged 2 years and older; PA–1: reduce the proportion of adults who engage in no leisure-time physical activity; and PA–2: increase the proportion of adults who meet current federal physical activity guidelines for aerobic physical activity and for muscle-strengthening activity.

Research conducted prior to the implementation of the health intervention suggested that gender-based strategies were especially important to address for this health intervention. Hence, the UWAG project approached the needs assessment using gender-based initiatives in order to analyze how gender norms impact health behaviors. The Phase I needs assessment explored questions related to the intersection of sex, gender, culture, body weight, and healthy behaviors. One of the reasons gender-based strategies were important to incorporate in this health intervention is that providing women with needed resources allows them to make more healthful choices. Also, educating and empowering women has positive influences on their families and communities. In Phase I, the decision was made to focus the health intervention program on obesity and health behaviors (diet/exercise) for Phase II application. Also, through a partnership with the communities, during Phase I the project coordinators decided that every woman would receive services so as to keep the community interest in mind. It was important to the community that each woman received the benefits of this health intervention. Thus, instead of a control group, the project was changed to a high- versus low-intensity health intervention program.

Recruitment for the study was performed by community wellness coaches through convenience sampling at community events, and after that, snowball sampling through friends and relatives of participants. In order to be eligible, participants had to self-identify as a member of one of the five cultural communities, be 18 years of age or older, be able to speak English, Spanish, or Kirundi, and be willing to participate in a 1-year randomized study. Women receiving wellness coaching through the Utah Cancer Control Program's BeWise Program or other similar coaching programs were ineligible to participate.

The data came from the baseline survey and 12-month follow-up data. The baseline survey gathered demographic, socioeconomic, biometric, behavioral, and time-use characteristics before the intervention began. As of February 10th, 2015, 399 women had completed the baseline survey, and were eligible for inclusion in this analysis. The breakdown of cultural group membership in the sample, at baseline, was 85 Pacific Islander immigrants, 62 American Indians/Alaskan Natives, 80 African Americans, 104 Hispanic/Latinas, and 68 African immigrants.

5.4 UWAG Results and Economic Assessment

5.4.1 Study Sample

As of February, 2015, 496 baseline surveys were conducted in total and 399 baseline surveys were completed (Table 5.1).[24] The number of completed 4-month follow-up surveys is 227, with 121 high-intensity group women and 106 low-intensity group women. At 8 months, 203 total surveys were conducted (103 high-intensity group, 100 low-intensity group); of the total, 165 are complete (89 high-intensity, 76 low-

[24] Whether this discrepancy between number of surveys conducted and number of surveys completed is due to retention issues is unclear at this time.

intensity). At 12 months, 149 surveys have been conducted (79 high- intensity, 70 low-intensity), and of those, 141 are complete (74 high-intensity and 67 low- intensity).

5.4.2 Descriptive Statistics

Descriptive statistics for the sample overall and by cultural group membership are provided in Tables 5.2 and 5.3. Excluding those with missing data for analytic variables, the resultant sample size was 344 women (Table 5.2). The average age is 41 (standard deviation: 13.43); 53% live in low-income households (defined as monthly income less than or equal to $2,000), 56% are married or living with their partners, 64% have at least a high school degree or more, and 59% are employed (working full or part time for an employer or are self-employed).

Being normal weight, overweight, and obese is measured by body mass index (BMI) levels; BMI between 18.5 and 24.9 is normal weight, BMI between 25 and 29.9 is overweight, and BMI greater or equal to 30 is obese. Various grades of obesity exist where Grade I obesity is a BMI between 30 and 35.9, Grade II obesity is a BMI between 35 and 39.9, and Grade III obesity is a BMI greater or equal to 40. From the overall sample, approximately 17% are normal weight, 25% are overweight, and 58% are obese. Of the obese, 31% are Grade I obese, 13% are Grade II obese, and 14% are Grade III obese. Regarding physical activity, 42% of this group meet the CDC (Center for Disease Control and Prevention) requirement for daily physical activity, which is 6% less than the fraction of all adults who meet the CDC's 2008 Guidelines (CDC, 2014).

There are substantial differences between the groups concerning socioeconomic and demographic characteristics (Table 5.3). For example, 90% of African immigrants live in low-income households, followed by 66% of American Indian/Alaskan Native women and 62% of Hispanic women; on the other hand, only 24% of Pacific Islanders and 36% of African American women live in low-income households. Discrepancies also arise regarding education: 86% of African Americans and 81% of American Indian/Alaskan Native have at least a high school degree. However, only 42% of African immigrants have at least a high school degree (Hispanic: 55%, Pacific Islander: 53%). ANOVAs were statistically significant for differences between the cultural groups for income and education level.

African immigrant, Pacific Islander, and American Indian/Alaskan Native have similar percentages of around 53-57% of the population being married; African American women have the lowest percent of women who are married (36%), and Hispanics appear to be above average with 74% married or living with a partner. The percentage of women who are employed is consistent for the African immigrant, African American, and American Indian/Alaskan Native populations as roughly 50% of them are employed; Pacific Islander women have the highest rate of employment at 70%. Statistically significant results were obtained for marital status.

Hispanics have the lowest percentage of women who meet the CDC's physical activity requirement as only 20% of the population engages in such activity; in contrast, 53% of American Indian/Alaskan Native, 51% of Pacific Islander, 48% of American immigrant, and 46% of African American women meet the requirement. Statistically significant differences between the cultural groups were found for physical activity.

There is great variation in BMI categories as well where normal weight is defined by a BMI that is between 18.5 and 25. Overweight is defined as a BMI between 25 and

30 and obese is a BMI greater or equal to 30, for all cultural groups besides Pacific Islanders; for Pacific Islanders, normal weight is defined as a BMI between 18.5 and 26, overweight is between 26 and 32, and obese is greater or equal to 32. For those who are in the normal weight category, the highest percentage is among African immigrant women (25%), followed by Hispanic (20%), African American (14%), American Indian/Alaskan Native (13%), and Pacific Islander women (11%). Concerning those women who are overweight, African American women have the highest percentage (28%), followed by Hispanic (27%), American Indian/Alaskan Native (26%), African immigrant (23%), and Pacific Islander (16%). ANOVAs showed no statistical differences among the cultural groups for normal weight or overweight women. In the obese category, 73% of Pacific Islander women are obese compared to 60% of American Indian/Alaskan Native, 58% of African American, 53% of Hispanic, and 52% of African immigrants. ANOVAs showed statistically significant results for the obese category.

5.4.3 Total Costs of the UWAG Program

Costs associated with the health gains are the incremental costs between no intervention and those accrued from the program. Total costs and cost per person of the UWAG program over the 3 years that it has been in progress are shown in Table 5.4 Costs are based on the number of conducted surveys.[25]

UWAG total costs were based on the following calculations: survey costs (baseline survey and 4-12 month follow up surveys). Total costs for baseline surveys were $42,160. Follow-up survey interview fee-for-services costs included costs

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[25] Surveys that have not yet been completed (at baseline, 4 months, 8 months, and 12 months) were included in the survey costs data.

associated with scheduling, data collection, and data entry. Total costs for the follow-up surveys for the low-intensity group equal $17,901 while total costs for the high-intensity follow-up surveys amounted to $49,419.[26]

Costs associated with coaching included coach training, monthly wellness coach meetings, meetings for coaches with community leaders, coach toolkits, and group activities (high-intensity only). Monthly wellness coach meetings amounted to $8,330, monthly meeting with the CFU leader amounted to $4,165, monthly group activities costs $18,500, toolkit costs totaled $9,750, and training costs per coach cost $11,000. Administrative costs for the 3 years of work amounted to $182,994. The annual community budget, available for each of the five communities, takes the following into account: an allowance (for travel, childcare, other miscellaneous expenses), cash for data collection, an athletic bra for each participant; course incentive: new leaf participants (health tools to support meeting goals), health fair costs, CFU leader budget, a balance amount, and wireless cards for each community.

Expenditures for "cash for data collection" equaled $26,360.[27] Allowances for each community totaled to $15,000, health fair costs equaled $7,500, athletic bras costs $12,400.[28] Community leader expenses totaled $42,000, the community balanced amounted to $13,500, course incentives totaled $27,000. The wireless cards have not been distributed to all the communities as of yet; total costs have amounted to $2,250 for the wireless cards. It should be noted, however, that these estimates pertaining to costs associated with "community annual budgets" are likely to be an overestimation as most

[26] Completed annual follow-up survey costs have not yet been incorporated.

[27] This number may change if additional information becomes available whether or not the survey has to be completed in order to receive the cash for being part of the study.

[28] It is unclear whether or not those who did not complete the baseline survey received an athletic bra . This does not affect the per person, per year estimate but does impact the total costs.

of the communities have not spent this much to date.

Summing these components, the total cost of the program over the last 3 years is $490,229. As cost-effectiveness ratios (CER) pertain to per person, per year account, overall costs per person, per year were calculated based on the total costs (see Table 5.4). The number of women in the study were calculated as person-years, with anyone in the study for 4 months equaling 1/3 person-years, 8 months equaling 2/3 person-years, and 1 year equaling 1 person-year; given this, total person-years, 327, comprised the denominator.[29] The overall cost per person, per year equaled $744.[30]

5.4.4 Results: Physical Activity Gains

The Health and Human Services criteria was used to categorize physically active and physically inactive for adults aged 18-64, physically active means participating in at least 150 minutes of moderate intensity aerobic physical activity or 75 minutes of vigorous aerobic physical activity per week. Those meeting the guidelines were categorized as “physically active” in juxtaposition to those “physically inactive” who did not meet the guidelines. A third category, “insufficiently active,” was used to designate those who reported some physical activity but not enough to meet the physical active guidelines. Hence, “insufficiently active” means reporting greater than 0 minutes of physically activity per week but less than 2.5 hours every week.

Results of the intervention pertaining to physical activity levels are shown in Tables 5.5-5.7. For the 144 women from baseline who had completed the 1-year follow up survey, 34% went from being “physically inactive” to “physically active.” At baseline,

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[29] If we were to compute the person-years regarding “surveys conducted” instead of surveys completed, we would obtain total person-years of 392.

[30] For a detailed account of the per person, per year costs, see Table 5.7.

67.36% were inactive and 32.64% were active. By the end of the year, 44.44% were inactive and 55.56% were active. Not to exclude those women who increased their physical activity levels but did not reach the “physically active” category, the data showed that among those women, 21 were inactive and 31 women were insufficiently active; at 1 year, 7 were inactive and 45 were insufficiently active. Thus for the UWAG group, there was a 67% increase for women who went from physically inactive to insufficiently active (Tables 5.5-5.7).[31]

5.4.4.1 Results: Physical Activity Gains by Arm of Intervention

Breaking down the sample by low- versus high-intensity treatments, there was a 37.74% improvement in the high-intensity group (53 women were inactive at baseline and 33 women were inactive at the 1-year mark), with 74 total women in the sample (Table 5.6). There was a 30.95% improvement for the low-intensity group (42 women at baseline to 29 women at the 1- year mark); for the low-intensity group, there were 67 women who had completed the surveys (Table 5.6). Going from inactive to insufficiently active, there was a 30% improvement for the low-intensity group and a 27.27% improvement for the high-intensity group.[32] The low-intensity group therefore had greater improvements regarding changes from physically inactive to insufficiently active, whereas the high- intensity group has greater improvements going from physically inactive to physically active.

[31] We do not have a way to control for the fact that some women who were physically active went to being insufficiently active or inactive during this 1-year study. Hence, we estimate that there was at least a 34% improvement for the overall group.

[32] The program has also seen moderate success in reducing BMI levels. At baseline, there were 17 women in the normal weight category and by the end of the year, there were 25 women. There were 34 overweight women at baseline, which decreased to 28 for those who had completed the study. Gains in health by reduced BMI categories will be incorporated in future studies.

5.4.4.2 Results: Life Satisfaction and Happiness Scale

Measuring life satisfaction and happiness changes are potentially reinforcing factors to the QALY literature; these two quality of life questions were asked at baseline and 1-year follow up survey. Though not an independent assessment of cost-effectiveness in terms of a happiness index, it is, in some sense, a way to assess change in quality of life. At baseline, 6 women (4.26%) were very dissatisfied, 14 women (9.93%) were dissatisfied, 94 women (66.67%) were satisfied, and 27 women (19.15%) were very satisfied (n = 141). At the 1-year follow-up mark, 3 women (2.13%) were very dissatisfied, 12 women (8.51%) were dissatisfied, 90 women (63.83%) were satisfied, and 36 women (25.53%) were very satisfied (n = 141). After conducting a t-test to analyze whether the shift is statistically significant, results indicate that they are not.

At baseline, 3 women (2.13%) were very unhappy, 3 women (1.42%) were unhappy, 29 women (20.57%) were neutral, 67 women (47.52%) were happy, and 39 women (27.66%) were very happy. After the 1-year study, from this group, 2 women (2.13%) were very unhappy, 1 woman (0.71%) was unhappy, 15 women (10.64%) were neutral, 72 women (51.06%) were happy, and 39 women (27.66%) were very happy. From both the life satisfaction and happiness scale measures, we can conclude that the women are seeing higher levels of happiness, although the percentage of happiness attributable to the program versus exogenous factors is unclear. This shift, however, is not statistically significant.

Potential changes in level of happiness or life satisfaction were analyzed to test whether quality of life gains are observed with increased level of physical activity. Being dissatisfied and very dissatisfied were grouped as “not satisfied” and very satisfied and satisfied were grouped as “satisfied.” At baseline, 20 women were dissatisfied and 121 women were satisfied while 15 were dissatisfied and 127 were satisfied at the 1-year mark. We tested for the occurrence of satisfaction levels related to physical activity levels: at baseline, from those who are dissatisfied, 3 were active and 17 were inactive; at the 1-year mark, 12 women were active and 3 were inactive. Hence in terms of life satisfaction, we do not observe a difference in becoming physically active at the present time.

Potential increases in quality of life for these women can be ascertained from the level of happiness measure. At baseline, 35 women were classified as being unhappy (i.e., very unhappy, unhappy, or neutral) and 106 women were classified as being happy (i.e., happy or very happy); at the 1-year mark, the number of women who were unhappy decreased to 18 and the number of women who were happy increased to 124. At baseline, from the women who were unhappy, close to 86% were inactive and approximately 14% were active. At the 1-year mark, from the women who were unhappy, the percent of women who were inactive dropped to 39% and those who are active increased to 61%. Given more future data, these quality of life changes can potentially be used as an alternative outcome to QALYs.

5.5 Results: Cost-Effectiveness Ratio

Cost-utility analysis (CUA) is a form of CEA, and based on assessments of health states according to various methods, often in terms of QALYs (Cohen & Reynolds, 2008). The outcome of cost-effectiveness analyses is expressed as a ratio. The cost-effectiveness ratio (CER), where the denominator is the gain in health and the numerator, is the cost associated with the health gain. In order to measure gains in health, quality-adjusted life years (QALYs) are used as they are the preferred measure of effectiveness. The formula for the cost-effective ratio is given by:

$$\mathrm{CER} = \frac{\text{cost associated with health gain}}{\text{gain in health}}$$

Gains in health are measured by taking the difference between total expected quality-adjusted life years gained from the intervention and total expected QALYs with no intervention (Roux et al., 2008). QALYs measure both quantity and quality of life gained or lost by a disease or health intervention through measuring gains or losses in utility.[33] QALYs can be assessed through different methods including rating scale, standard gamble, and time trade-off (Torrance, 1986). Rating scales ask individuals to rate their state of ill health and have the advantage of being easiest to implement among the various techniques, but they are the most subjective. Standard gamble and time trade-off methods measure individuals' willingness to sacrifice life expectancy in order to be relieved of the symptoms and dysfunctions associated with a state (Nord, 1999).

No threshold determines whether an intervention is cost-effective. However, a consensus with little justification has emerged in the United States that a cost of less than or equal to $50,000 per average QALY gained is an acceptable standard; another widely used value is $100,000 per QALY (Grosse, 2008; Weinstein, 2008). No formal threshold has been formally adopted in the United States by the Centers for Medicare and Medicaid

[33] In order to obtain QALYs, individuals are asked about their preferences for various health states, and the utility is measured. The utility scale is a continuous measure from 0 (which reflects death) to 1 (which reflects full health). States defined as worse than death can also exist; if they did, they would have a negative utility value associated with them (Nord, 1999).

Services and has not been endorsed by the Panel on Cost-Effectiveness in Health and Medicine.

Gains in health, specifically meaning gains in QALYs from a physical health intervention, were taken from the literature; in particular, QALYs gained were taken from the Sun et al. (2014) article and Roux et al. (2008). Though the health interventions analyzed in the Roux et al. piece cannot serve as a direct measure for the UWAG health intervention (e.g., one intervention targeted older women, one sampled University staff members and students, one focused solely on obese men and women, and another consisted of both men and women where 45% of the sample was minority group members), there were two health individually-adapted health intervention programs analyzed. Given this, the results obtained regarding QALY improvements from these individually adapted health interventions will be utilized as a sensitivity analysis in this chapter. A limitation to the Roux et al. study for the UWAG health intervention economic analysis is that it did not quantify QALYs gained from different thresholds of physical activity levels nor did it disaggregate results by gender/race.

Sun et al. quantified QALYs gained from different thresholds of physical activity gains (i.e., physically active, physically inactive, and insufficiently active) and quantified QALY gains for men versus women. This is an important point to emphasize because the results of any physical intervention are more than likely to be different between genders. A noticeable limitation regarding the Sun et al. study is that the study sample consisted of men and women between the ages of 45 and 79 who had, or were at increased risk of having, knee osteoarthritis. Though one of the risk factors for knee osteoarthritis used in the study was obesity, this study population does not mirror that of the UWAG population.

Sun et al. (2014) quantified QALYs from rating scales, specifically the Short Form Health Survey. The Sun et al. study shows that higher QALYs were gained by those who were engaged in higher physical activity; however, moving from inactive to insufficiently active also had positive health outcomes. The study concluded that total QALYs gained for women, age-adjusted, over the 2 years were 0.203 (95% confidence interval: 0.127, 0.279); hence per year, QALYs gained for women amounted to, on average, 0.1015 (0.0635, 0.1395). After adjusting for socioeconomic status, the QALYs gained over the 2-year period were 0.199 (0.117, 0.281); hence, per year, for females, QALYs gained amounted to 0.0995 (0.0585, 0.1405).

Over the 2 years, looking at the full cohort and analyzing age-adjusted difference, for females, QALYs improved 0.084 (0.039, 0.129) for those who went from insufficiently active to active; hence per year, the QALYs gained going from inactive to insufficiently active totaled 0.042 (0.0195, 0.0645). Taking SES factors into account, QALYs gained from going from inactive to insufficiently active equaled 0.091 (0.042, 0.140); hence per year, QALYs gained were 0.0455 (0.021, 0.07).

5.5.1 Cost-Effectiveness Ratios for Overall Study

The total gains in health can be measured by the QALYs gained by increasing physical activity times the percentage of women who went from being physically inactive to physically active; for the overall study, total gains equal 0.1015*34%. An analysis of the cost-effectiveness for the overall study, using the age-adjusted QALYs, shows a cost-effectiveness ratio of $21,559 as obtained by $744/(0.1015*34%). A sensitivity analysis on this result, using the confidence interval (CI) values for QALY values, shows CERs between $15,686 and $34,460.[34] Utilizing the socioeconomic status QALYs from the Sun et al., the resulting CER is $21,992 (CI: $15,575 - $37,406).

For women who went from physically inactive to insufficiently active, we find the following results: using the age-adjusted QALYs, the CER equals $26,582 (CI: $17,309 - $57,254) and using the socioeconomic-status adjusted QALYs, the CER equals $24,537 (CI: $15,949 - $53,164). For the overall study, the program is cost-effective for both those who went from physically inactive to physically active and those who went from physically inactive to insufficiently active, using the $50,000 per QALY standard.

A sensitivity analysis was conducted by utilizing the QALY gained from the two individually adapted health intervention programs provided by Roux et al. The QALYs gained from these health interventions were 0.064 and 0.058, per year; thus the CERs for the UWAG health intervention would equal $34,191 per QALY and $37,728 per QALY, respectively. Again the results show that the UWAG program is cost-effective, using the $50,000 per QALY standard.

5.5.2 Cost-Effectiveness Ratios for Treatment Groups

Analyzing the results by treatment group, per woman per year costs associated with the high-intensity program are $692.70 and per woman per year costs of the low-intensity program are $571.36. Utilizing the age-adjusted QALYs gained (QALYs = 0.1015 per year) and analyzing the group of women that went from physically inactive to physically active, the high- intensity CER equals $18,083 (CI: $13,157 - $28,905) and the low-intensity CER equals $18,188 (CI: $13,234 - $29,072).

[34] The cost-effectiveness ratios as well as the costs are rounded to the nearest whole dollar.

Here, we observed that the cost-effective ratios for low- and high- intensity treatment groups are very close, even though the high-intensity had higher costs per person. The CERs are close for the low-intensity group because though the high-intensity group had greater costs per person, it also had a greater percent of improvements in the percent of women who went from physically inactive to active. Using the socioeconomic-status adjusted QALYs (QALYs gained = 0.0995), the CER for the high-intensity group is $18,447 (CI: $13,064 - $31,375) and CER for the low-intensity group is $18,554 (CI: $13,139 - $31,557). The cost-effectiveness ratio results show that both intervention groups are cost-effective for those women going from physically inactive to physically active.

Focusing on the CER for those who went from inactive to insufficiently active, 30% in the low-intensity group went from physically inactive to insufficiently active and 27.27% in the high-intensity group went from physically inactive to insufficiently active. For the high-intensity group, applying the age-adjusted QALYs, the CER is $60,479 ($39,382 – $130,264) and using the socioeconomic-adjusted QALYs, the CER is $55,828 ($36,288 - $120,960). For the high-intensity group, gains attained from going from physically inactive to insufficiently active are not cost-effective by the current standard.

For the low-intensity group, the CER going from physically inactive to insufficiently active, using age-adjusted QALYs, is $45,346 ($29,528 - $97,668); using the socioeconomic-status QALYs, the CER is $41,558 ($28,207 - $90,692). Except for the results gathered from conducting the sensitivity analysis for the QALYs used in the analysis, we conclude that for those in the low-intensity treatment group, it is cost-effective going from inactive to insufficiently active (Tables 5.8 and 5.9). [35]

5.6 Discussion and Conclusion

This study seeks to extend the literature, demonstrating that wellness coaching interventions conducted through engaged community partnerships may be a critical component in enhancing healthful lifestyles with resulting reductions in net societal costs. The result from the cost-effectiveness ratio indicates positive evidence of cost-effectiveness for the UWAG study, as a CER below or equal to $50,000 is said to be cost-effective. Of note, results for the UWAG intervention, thus far, fit the ranges reported in the literature, as shown in Table 5.10. This study is unique in the sense that previous studies on physical intervention programs have not focused on minority/cultural groups, as they are often harder to target. In fact, UWAG is the first to show similar benefits through an intervention among such high-risk groups.

We faced certain limitations in the study. We have selection issues as all those who participated in the program volunteered to be participants for a health intervention program. As we do not have associated QALY measures for this group of women, or for this particular segment of the population, this study has to draw on the literature for a quantitative measure of QALYs. There are two studies, Roux et al. (2008) and Sun et al. (2014), that have accessed QALYs gained from physical activity.

Roux et al. calculated QALYs gained from different physical activity intervention programs. These seven intervention programs were classified as either community-wide campaigns, social support, individually adapted health behavior change programs, and

[35] Table 5.8 shows all the cost-effectiveness ratios for the study, depending on QALY used and intervention arm, for the inactive to active results. Table 5.9 shows all the cost-effectiveness ratios for the study for those going from inactive to insufficiently active.

enhanced access to places for physical activity combined with information outreach activities. Roux et al. calculated QALYs for "no intervention" scenarios and QALYs associated for each program so as to measure incremental QALYs gained from these health interventions. Lifetime (medical) costs were estimated to be around $195,000 per person; however, the authors do not take into account that medical costs are bound to be different when analyzing both gender and age. Also the authors used a Markov model to estimate lifetime costs but did not separate the estimations by race or gender.

When calculating incremental QALYs gained from the program versus no intervention, the study does not take into account that QALYs gained from increases in physical activity are shown to be different between gender and race. Also it is unclear how total QALYs for each physical health intervention program listed were calculated, specifically what factors influenced the QALYs gained (QALYs gained were between 0.014 and 0.102, depending on intervention program). Lastly, the results for the Roux et al. study are sensitive to the time-horizon, for their initial assessment was conducted over a 40-year time horizon; the authors note that shortening the analytic time-horizon (from the used 40 years) to 30, 20, or 10 years influenced cost-effectiveness outcomes substantially (Roux et al., 2008).

The second paper that quantified QALYs gained from physical activity increases is from Sun et al. (2014), which assessed QALYs gained for those who participated in an accelerometer ancillary study of the Osteoarthritis Initiative. Candidates were enrolled if they had, or were at increased risk of having, knee osteoarthritis and were between the ages of 45 and 79. Given this, the QALYs gained from physical activity are likely not be a direct reflection for the UWAG group, given that the UWAG population is composed of solely minority group women and are not participants in the Osteoarthritis Initiative. However, a strong point of this article is that the authors were sensitive to age and socioeconomic status. Thus, even though we do not have a direct measure relating to minority group women, we have, however, a QALY assessment that at least takes socioeconomic status into account. Given that the Sun et al. health intervention targeted those who had or were at risk of knee osteoarthritis, QALYs gained from physical activity level increases may be a liberal or conservative estimation in comparison to an adult who is not at risk of knee OA.

The article also states that it adjusts for socioeconomic status but physical activity gains are likely to have higher benefits for the UWAG group because they are all minority group women, which is another reason the QALYs gained number may be conservative. The estimates obtained may also be conservative given that other potential gains in health could be associated with this health intervention (i.e., gains in health from increased nutritional intake and decreased levels of BMI); this current study, however, did not incorporate QALYs gains from nutrition changes or QALYs gained from decreased levels in BMI, as further data are needed to assess those gains.

Initial results from the UWAG health intervention show changes in BMI levels; at baseline, regardless of physical activity levels, data show 17 women were normal weight, 34 women were overweight, 52 women were Grade I obese, 22 were Grade II obese, and 19 women were Grade III obese. At the 1-year mark, 25 women were normal weight, 28 were overweight, 54 were Grade I obese, 20 were Grade II obese, and 17 were Grade III obese. Initial assessments show that the number of normal weight women increased while the number of overweight women decreased; though the number of Grade I obese women increased, this could very well be because we saw that number of women who were Grade II obese and Grade III obese decreased (however, the changes are not statistically significant). Even though we have seen, thus far, positive results in increases in physical activity levels and reductions in BMI strata, it is uncertain as of yet how the UWAG study compares to other studies. Hence the question arises whether individually coaching-based interventions are worth the additional costs they warrant.

There could be other potential benefits that arise from this health intervention program that are not captured via QALYs gained from physical activity gains or BMI reductions. For instance, levels of happiness or life satisfaction could change through, for example, friendships or confidence gained from the program that would not be captured in the analysis. For all these reasons, the estimates presented may be conservative. Another reason why this analysis is potentially conservative is that spillover effects (e.g., a woman's family member becoming more active or eating more nutritious foods due to the program) cannot be captured; preliminary evidence show that in some cases, the spillover effects have helped family members lose weight.

This intervention was structured in an academic environment; hence there are ongoing research and direct administrative costs that may not otherwise be present. There is also, naturally, a learning curve associated with any intervention and therefore some of the costs associated with the basic intervention might not be included as learning increases. For this reason, some of the research costs may have been included when they should not have. In that regard, some of the costs included may provide for a conservative estimate. For instance, at the beginning of the study, those collecting data at baseline were paid by hour instead of the fee-for-service. However, the fee-for-service payments have proven to be far more effective and cost-saving; these are important observations to make for further community-based participatory research projects. Our study results will be conservative as they include only the direct effects on recruits and do not capture secondary effects on the children or partners of participants.

On the other hand, goodwill provided by community members is not taken into account as it is an intangible asset but might command a price; for this reason, the estimates may be liberal. Overall, gains from this program have been seen in both the number of women who went from inactive to active and from inactive to insufficiently active. Further gains were seen, though not analyzed or incorporated in this analysis, regarding decreases in BMI levels and increases in the number of women who were more satisfied in their life and happier as well. The program is cost-effective, for both the low-intensity and high-intensity groups. Future extensions that will be incorporated for the UWAG project are adjustments related to attrition rates and conducting further sensitivity analysis. Also, the CERs were broken down by intervention arm for this study, but they can be conducted for each cultural group in the study once more data are collected.

Lastly, the cost-effectiveness assessment was made regarding changes from baseline to the 1-year mark of the program. However, we will need to pay attention for long-term goals as well, mainly, is the program sustainable? After the coaching intervention has been complete, do we know whether the women will adhere to the new lifestyle or revert back to old habits? However, we have seen that this tailored coaching intervention, targeting minority group women, is cost-effective and has warranted important aspect regarding community engagement.

Table 5.1. Number of Participants

	Number of Surveys Conducted	**Number of Surveys Completed**
Baseline	496	399
Four Months	321 High-intensity: 140 Low-intensity: 181	227 High-intensity: 121 Low-intensity: 106
Eight Months	203 High-intensity: 103 Low-intensity: 100	165 High-intensity: 89 Low-intensity: 76
Twelve Months	149 High-intensity: 79 Low-intensity: 70	141 High-intensity: 74 Low-intensity: 67

Table 5.2 UWAG Means (SDs) and Percentages of Socioeconomic and Demographic Characteristics at Baseline (n = 334)

Variable	**Mean (SD) or Percentage**
Age	41 (13.64)
Monthly Income ≤ $2,000	53%
Married	56%
High School Education (or more)	64%
Employed	59%
Walking Environment	9.21 (3.60)
Food Environment	6.98 (3.90)
Meets Physical Activity Requirement	42%

Note: Employed describes those women who are working full or part time for an employer or are self-employed.

Table 5.3 UWAG Means (SDs) of Socioeconomic and Demographic Characteristics by Cultural Group

Variable	African Immigrant (*n* = 68)	African American (*n* = 80)	Hispanic (*n* = 104)	Pacific Islander (*n* = 85)	American Indian/ Alaskan Native (*n* = 62)
Age	35.69 (11.12)	48.41 (15.36)	41.18 (10.37)	34.61 (12.5)	41.90 (12.53)
Low Income	89.58%	36.49%	62.35%	24.32%	66.04%
Married	54.17%	37.84%	74.12%	56.76%	52.83%
High School Education (or more)	41.67%	86.49%	55.29%	52.70%	81.13%
Employed	50%	66.22%	51.76%	70.27%	50.94%
Meets Physical Activity Criteria	47.92%	45.95%	20%	51.35%	52.83%
Normal Weight	25%	13.51%	20%	10.81%	13.21%
Overweight	22.92%	28.38%	27.06%	16.22%	26.42%
Obese	52.08%	58.11%	52.94%	72.97%	60.38%
ANOVA RESULTS					
Age	13.46	Employed	2.62	Obese	2.09
Low Income	19.82	Meets Physical Activity Criteria	6.16		
Married	5.67	Normal Weight	1.50	***F*-critical**	**1.94**
High School Education (or more)	11.24	Overweight	0.95		

Table 5.4. Total Costs of UWAG Health Intervention Program (3 Years)

TYPE	TOTAL COST	COST PER PERSON
Baseline Surveys ($85 per person * 496 surveys)	$42,160	$85
Low Intensity Follow-Up Surveys (Low-Intensity) ($51 per survey; 4 month, 8 month, and 12 month totals were $9231, $5100 and $3570, respectively)	$17,901	$51
High Intensity Follow-Up Surveys ($51 per survey at 4, 8, and 12 months and $34 per survey at 1, 2, 3, 5, 6, 7, 9, 10, and 11 months; total costs for those in the high-intensity program at 4, 8, and 12 months were $21,420, $15,912 and $12,087, respectively)	$49,419	$153.48
Coach Training Costs ($1,000 per coach * 11 coaches)	$11,000	$11.21
Monthly Wellness Coach Meetings (245 months *$34 per month per coach)	$8,330	$8.49
Monthly Meeting Between Coaches and Community Leaders (245 months *$17 per month per coach)	$4,165	$4.25
High Intensity Monthly Group Activities (185 months * $100 per month per coach)	$18,500	$18.86
Wellness Coach Toolkits ($975 each * 2 per community * 5 communities)	$9,750	$9.94
Administrative Costs	$182,994	$186.54
Athletic Bra ($25 per woman * 496 women)	$12,400	$25
Cash for Data Collection ($20*791 + $40*141)	$26,360	$80.61
Allowance ($1,000 per community * 5 communities * 3 years)	$15,000	$15.29
Health Fair Costs ($500 per community * 5 communities * 3 years)	$7,500	$7.65
CFU Leader ($2,800 per year * 5 leaders * 3 years)	$42,000	$42.81
Balance ($900 per community * 5 communities * 3 years)	$13,500	$13.76
Course Incentives ($1800 * 5 communities * 3 years)	$27,000	$27.52
Wireless Card ($500 * 3 cards * 1.5 years)	$2,250	$2.29
TOTAL COSTS (3 Years)	$490,229	$743.70

Table 5.5. Physical Activity Results All Women

	Baseline	One Year		Baseline	One Year
Inactive	97	64	**Inactive**	21	7
Active	47	80	**Insufficiently Active**	31	45

Table 5.6. Physical Activity Results by Intervention Arm (Inactive vs. Active)

High Intensity	Baseline	One Year	**Low Intensity**	Baseline	One Year
Inactive	53	33	**Inactive**	42	29
Active	21	41	**Active**	25	38

Table 5.7. Physical Activity Results High- and Low-Intensity
Group (Inactive vs. Insufficiently Active)

High Intensity	Baseline	One Year	**Low Intensity**	Baseline	One Year
Inactive	11	3	**Inactive**	10	3
Insufficiently Active	17	28	**Insufficiently Active**	13	20

Table 5.8. CER for UWAG Program (Inactive to Active)

QALY used	Overall Program	High-Intensity Arm	Low-Intensity Arm
Age-adjusted	\$21,559 (\$15,686 - \$34,460)	\$18,083 (\$13,157 - \$28,905)	\$18,188 (\$13,234 - \$29,072)
Socioeconomic Status	\$21,992 (\$15,575 - \$37,406)	\$18,447 (\$13,064 - \$31,375)	\$18,554 (\$13,139 - \$31,557).

Table 5.9. CER for UWAG Program (Inactive to Insufficiently Active)

QALY used	Overall Program	High-Intensity Arm	Low-Intensity Arm
Age-adjusted	$26,582 ($17,309 - $57,254)	$60,479 ($39,382 – $130,264)	$45,346 ($29,528 – $97,668)
Socioeconomic Status	$24,537 ($15,949 - $53,164)	$55,828 ($36,288 - $120,960)	$41,858 ($27,207 - $90,692)

Table 5.10. CER for Physical Activity Intervention Programs

Study	**Cost-Effectiveness Ratio**
Reger (2002)	$14,286
Lombard (1995)	$27,373
Linenger (1991)	$28,548
Jeffery (1998)	$29,759
Kriska (1986)	$39,690
Knowler (1992)	$46,914
Young (1996)	$68,557

CHAPTER 6

CONCLUSION

The literature regarding the economic costs of obesity has primarily focused on the direct costs of obesity. Less attention has been paid to the indirect costs of obesity, where the focus has been confined to measuring lost resources/productivity in the workplace. In this dissertation, I expand on the measurement of the indirect costs of obesity by focusing on those costs pertaining to household productivity losses and potential labor market outcomes, as measured by the relationship of occupational status and BMI levels. These costs are important to recognize because of the significant economic and societal burdens they impose. As such, it is critical to develop a more complete accounting of the overall costs of obesity and assess the cost effectiveness of one intervention designed to remediate them.

Focusing on the nonmarket costs of obesity, particular those pertaining to household productivity differences among women, this study provides evidence that being overweight and obese decreases time spent in home production. The results in Chapter 3 suggest that the per person nonmarket costs translate into $354 per overweight woman and $846 per obese woman, per year. Annually for the United States, these figures translate into over $10 billion lost for overweight women and over $32 billion lost for obese women. Given that housework differences are present in relation to race/ethnicity, the question as to whether these differences are a function of the housework obesity penalty rather than racial/cultural difference in housework was studied in Chapter 4. The results showed no statistically significant results for the coefficients on the BMI strata interaction variables for non-Hispanic Black, non-Hispanic Asian, or Hispanic women. Therefore, being obese matters for non-Hispanic Black women, non-Hispanic Asian women, and Hispanic women the exact same way it matters for non-Hispanic White women.

One limitation to this study that should be addressed is how household production was measured and the resulting implications that were made. Theoretically speaking, there are two different methods of valuing nonmarket household production: the output and input approach. Measuring housework through the output approach places a monetary value on all of the outputs that a household produces, such as the number of meals prepared. For this approach, one must identify the goods and services produced by households for their own consumption and find market substitutes and the associated prices for these goods and services (Chadeau, 1992). Given these limitations, the output approach has only been implemented in a few countries due to lack of data. On the other hand, the input approach places a monetary value on household production by measuring the labor inputs directly without having to estimate total household production (Chadeau, 1992). This study utilized the input approach, measuring household production by time spent in housework rather than outputs produced by households.

One assumption that was made in regard to nonmarket costs of obesity is that from the results obtained, it is assumed that the marginal productivity of housework for overweight and obese women is less than that for normal weight women. As such, it is assumed that overweight and obese women who are doing less housework than normal weight women are generating fewer home produced goods. However, this may not be true. It would be of great use to further examine this limitation by disaggregating time spent in housework to analyze where time differentials occur most; for example, are overweight/obese women more likely to spend less time on meal preparation and clean up than normal weight women? If so, are there family implications that stem from this? Given that the analysis showed that there are time differentials in housework by BMI strata, it would also be of great benefit to start investigating what overweight/obese women are doing with the time they are not spending in housework.

Nonmarket production is important to take into account as focusing solely on market activities for the inclusion of gross domestic product (GDP) leads to limitations of national accounts. In fact, one study shows that incorporating household production would raise nominal GDP by 26%, in 2010 (Bridgman, Dugan, Lal, Osborne, & Villones, 2012). Also, an important point is that home production reduces income inequality (Bridgman et al., 2012; Frazis & Stewart, 2006). Estimates indicate that individuals, regardless of household income, spend similar amount of time on household production. The correlation between family income and home production hours was shown to be very low, especially among women. Hence, increasing time spent in home production increases income of low income families proportionately more than high income families, which decreases inequality (Bridgman et al., 2012).

Given that there are both medical consequences of obesity (e.g., comorbidities and reduced quality of life) as well societal consequences (e.g., stigmas and discrimination), including nonmarket costs of obesity adds another element to the already substantial burden: increased income inequality among those who are overweight and obese. Thus, going forward, a more complete picture of the obesity epidemic should incorporate these more subtle, but equally important costs.

Another important element to take into account with the obesity epidemic is that it not only has individually-level effects, but also has societal effects. We know that obesity costs approximately $147 billion in direct costs annually, close to $73 billion in indirect costs annually, and an additional $32 billion in household productivity losses. These costs, in part, place a large burden on the public sector (e.g., Medicare, Medicaid, and other government programs), therefore having tax-burden implications. Obesity, therefore, creates market failures in the form of negative externalities, where the costs of obesity have third-party implications. It is not solely the obese person who pays, but society as well.

There is also the question of what the societal burden is beyond the medical costs. Are there family life implications of obesity? Does obesity have an influence on child outcomes? If, for example, obese women are more likely to purchase meals outside of the home instead of spending time in meal preparation, we could see potential effect on children in these households. Knowing that child obesity rates have increased significantly in the past 2 decades, particularly among minority groups, there is potential that a particular component from this study could shed some light on the subject matter. This would be an interesting extension of the current research project.

As such, there are many potential reasons why it is of great importance to have targeted interventions to decrease health disparities, especially for vulnerable populations. Community-based participatory research and health interventions, such as the UWAG program, hold great promise for increasing community engagement and social action has shown to increase the likelihood of a health intervention's success. Results from Chapter 5 indicate that the UWAG health intervention is cost-effective and improvements are noted in terms of increased physical activity and decreases in BMI levels. Given that there are many possible societal costs of obesity and given that the UWAG cost-effectiveness conducted focuses solely on physical activity changes, results are conservative. Thus, including aspects such as potential changes in housework among the UWAG group could benefit our study greatly.

Further extension of the study will include a cost-benefit analysis (CBA) of the UWAG study. When conducting the CBA, the costs associated with obesity should not solely include the direct costs and the classically-defined indirect costs, but need to include the indirect costs pertaining to nonmarket household productivity losses as well. Another critical point when discussing any health intervention program is whether the health changes observed (e.g., increased physical activity levels) are sustainable over the long-term or whether participants revert back to old lifestyles after the health intervention program has been completed. Some form of follow-up survey would be quite beneficial in this regard.

In conclusion, results obtained in this study indicate that the costs of obesity, particularly regarding household productivity losses among overweight and obese women, are quite substantial. Also, these costs are likely to extend beyond the household, given the potential spillover effects. When conducting cost-effectiveness analyses for health interventions, such as the UWAG program, they should include measures of these additional indirect costs in order to achieve a full accounting of cost-effectiveness.

APPENDIX A

MULTICOLLINEARITY DIAGNOSTICS

Number	**Eigenvalue**	**Condition Index**	**BMI**	**AGE_CAT**	**DAY_CAT**	**EMPSTAT_CAT**	**EDUC_CAT_D**
1	7.64131	1	0.002	0.00359	0.00374	0.00298	0.00388
2	1.14967	2.57809	0.000465	0.0233	0.0017	0.02276	0.00473
3	0.97999	2.79237	8.66E-06	0.00000234	0.00013289	0.00847	0.00093535
4	0.80661	3.07788	0.000952	0.01925	0.00122	0.7178	0.01406
5	0.60242	3.5615	0.000775	0.10955	0.00196	0.00192	0.00578
6	0.39453	4.40094	0.00132	0.11573	0.0315	0.06837	0.17774
7	0.32526	4.84694	0.01405	0.00227	0.54238	0.06353	0.28702
8	0.26732	5.34653	0.00024	0.39583	0.12925	0.00211	0.2948
9	0.23654	5.68366	0.000305	0.17971	0.00132	0.00352	0.00041169
10	0.19212	6.30666	0.02943	0.00748	0.10622	0.00712	0.15098
11	0.15911	6.92996	0.0461	0.01371	0.03583	0.01477	0.04667
12	0.14179	7.34101	0.11061	0.12337	0.09027	0.00012585	0.00683
13	0.10332	8.59967	0.79374	0.00621	0.05448	0.08652	0.00616

MARITAL STATUS	TENURE CATEGORY	NUMBER OF CHIDLREN	RACE	GENHEALTH	HOLIDAY	POVERTY	KID1TO2
0.00366	0.00265	0.00334	0.00347	0.00217	0.000361	0.0027	0.00171
0.00028374	0.00433	0.07857	0.00896	0.00091694	0.01629	0.00901	0.35439
0.00006181	0.00036354	0.00044299	0.00057095	0.00025371	0.96955	0.00077613	0.00529
0.00158	0.00007047	0.00272	0.00001098	0.00233	0.01202	0.00311	0.03949
0.00292	0.00344	0.20638	0.01539	0.00001351	0.000144	0.01207	0.55513
0.28109	0.03777	0.12064	0.00224	0.00070156	0.000105	0.00008499	0.00242
0.01199	0.00017414	0.0248	0.00053059	0.00121	0.000098	0.01206	0.02768
0.00016549	0.00221	0.16317	0.24381	0.00056129	0.000032	0.00177	2.14E-06
0.30035	0.00009882	0.27646	0.52824	0.00021188	0.000134	0.02187	6.103E-05
0.37461	0.20494	0.01291	0.18306	0.04027	0.000002	0.16708	0.00485
0.00003691	0.31561	0.11028	0.00431	0.01531	0.000085	0.73429	0.00345
0.0175	0.38089	0.00027514	0.008	0.49288	0.000305	0.02234	1.21E-07
0.00576	0.04746	0.00000119	0.00142	0.44318	0.086036	0.01285	0.00554

APPENDIX B

2SLS WEIGHTED PARAMETER ESTIMATES OF TOTAL HOUSEWORK FOR NON-HISPANIC WHITES AND NON-HISPANIC BLACK

Variable (*p<0.10, **p<0.05)	**Parameter Estimate**	**Standard Error**	***t* Value**	**Pr > |t|**
Intercept	259.58**	54.12	4.8	<.0001
BLACK_NH	-14.81	28.58	-0.52	0.6044
BMI	-1.19	1.93	-0.62	0.5356
BMI_BLACK	-1.26**	0.58	-2.18	0.029
AGE_CAT	-6.90*	3.87	-1.78	0.0743
AGE_BLACK	16.54*	9.53	1.74	0.0825
DAY_CAT	-31.06**	3.61	-8.6	<.0001
DAY_BLACK	9.26	9.15	1.01	0.3114
HHTENURE	-14.71**	4.41	-3.33	0.0009
TENURE_BLACK	7.34	9.12	0.81	0.4208
EMPSTAT_CAT	-90.99**	4.19	-21.7	<.0001
EMPSTAT_CAT_BLACK	20.52*	10.76	1.91	0.0565
EDUC_CAT_D	-12.88**	3.68	-3.5	0.0005
EDUC_CAT_D_BLACK	21.44**	8.96	2.39	0.0168
MARST_CAT_D	28.43**	3.92	7.26	<.0001
MARST_CAT_D_BLACK	8.06	9.37	0.86	0.3898
HH_NUMKIDS	47.78**	1.83	26.11	<.0001
KIDS_BLACK	-15.32**	3.98	-3.85	0.0001
HOLIDAY	36.90**	12.37	2.98	0.0029
HOLIDAY_BLACK	-57.84*	30.31	-1.91	0.0564
GENHEALTH_CAT	24.75**	5.54	4.47	<.0001
GENHEALTH_BLACK	-18.27	11.38	-1.61	0.1084
POVERTY	-2.27	4.68	-0.48	0.6279
POVERTY_BLACK	-20.26**	10.08	-2.01	0.0444
KID1TO2	76.87**	7.02	10.94	<.0001
YOUNGKID_BLACK	-38.81**	18.50	-2.1	0.036
R-Square/Adj.R-Square	0.206/0.204	*F* Value	111.06	

APPENDIX C

2SLS WEIGHTED PARAMETER ESTIMATES OF TOTAL HOUSEWORK PLUS TRAVEL FOR NON-HISPANIC WHITES AND NON-HISPANIC BLACK

Variable	**Parameter Estimate**	**Standard Error**	***t* Value**	**Pr > |t|**
Intercept	277.04**	55.44	5	<.0001
BLACK_NH	-16.52	29.28	-0.56	0.5726
BMI	-1.82	1.97	-0.92	0.3557
BMI_BLACK	-1.24**	0.59	-2.09	0.0363
AGE_CAT	-5.53	3.96	-1.4	0.1623
AGE_BLACK	16.38*	9.76	1.68	0.0933
DAY_CAT	-27.61**	3.70	-7.46	<.0001
DAY_BLACK	11.74	9.38	1.25	0.2106
HHTENURE	-14.04**	4.52	-3.1	0.0019
TENURE_BLACK	5.39	9.34	0.58	0.5638
EMPSTAT_CAT	-92.73**	4.30	-21.59	<.0001
EMPSTAT_CAT_BLACK	24.42**	11.02	2.22	0.0268
EDUC_CAT_D	-11.59**	3.77	-3.08	0.0021
EDUC_CAT_D_BLACK	21.08**	9.18	2.3	0.0217
MARST_CAT_D	28.65**	4.01	7.14	<.0001
MARST_CAT_D_BLACK	10.63	9.60	1.11	0.2681
HH_NUMKIDS	53.41**	1.87	28.49	<.0001
KIDS_BLACK	-16.36**	4.08	-4.01	<.0001
HOLIDAY	30.94**	12.68	2.44	0.0147
HOLIDAY_BLACK	-52.24*	31.05	-1.68	0.0925
GENHEALTH_CAT	23.60**	5.68	4.16	<.0001
GENHEALTH_BLACK	-17.12	11.66	-1.47	0.142
POVERTY	0.39	4.80	0.08	0.9347
POVERTY_BLACK	-20.26**	10.32	-1.96	0.0497
KID1TO2	77.21**	7.20	10.73	<.0001
YOUNGKID_BLACK	-28.81	18.96	-1.52	0.1286
R-Square/Adj. R-square	0.218/0.216	***p*<0.1,***p*<0.05**	*F* Value	119.16

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